Neighbourhood Effects on Educational Achievement: Evidence from the Census and National Child Development Study

Steve Gibbons

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Executive Summary

Area-targeted regeneration policy implicitly assumes that neighbourhoods make a difference to the prospects and achievements of individuals, especially children. Surprisingly, the evidence for this in the British context is sparse. To address this, we estimate the impact of a child's neighbourhood on his or her final educational attainments using data on British children who were teenagers during the 1970s. The paper is the first to look at the implications of neighbourhood influences for social mobility between generations in Britain. The focus is, however, quite specific: we ask whether the characteristics of a residential neighbourhood community for teenagers influences the final level of qualification they obtain. The emphasis is also on measurement of the size of these effects, and on separating out the causal effect of neighbourhoods, rather than seeking firm explanations.

The overall finding of this paper is that neighbourhoods do influence outcomes, regardless of family resources, but we find nothing to contradict the general consensus that neighbourhoods determine only a small proportion of the variation in individual outcomes, and that family background matters more. The benefits from aggregate improvements in neighbourhood quality *do* imply higher social benefits from tackling childhood disadvantage at the neighbourhood, rather than the family or individual level, but the evidence from this paper is that these additional benefits are quite small.

The key findings are:

- Children brought up in the same neighbourhood end up with similar educational attainments. This association is, however, quite weak. At most, the correlation between an individual's years in education and the average education of others who lived in the same ward in the 1970s is around 0.16. And this similarity in educational attainments is, in part, due to the children in the same neighbourhood having similar parents. Allowing for similarities in parental education alone halves this inter-neighbour correlation. An interpretation of these correlation coefficients is that a child could expect to increase his or her time in education by between 3.2 to 11.8 weeks if brought up amongst children destined to stay in education for 1.4 years longer than average.

- Another way of looking at this is to rank origin neighbourhoods in terms of the proportion of adults with A-levels and higher qualifications. We show that children from the top ten-percent of neighbourhoods, ranked in these terms, were between five and seven percentage points more likely to get A-levels themselves than children with similar family backgrounds living in neighbourhoods ranked in the bottom 10%. Children from educationally advantaged communities are also less likely to end up with no qualifications.

- These effects do not operate purely through the quality of local schooling or through association with peer-group pupils from better backgrounds attending the same school. Residential neighbourhood has an impact over and above anything related to local secondary school performance.

- One implication of this relationship is that a child brought up in a neighbourhood ranked at the bottom of the educational hierarchy would need parents educated to something like degree level to give him or her the same educational opportunities as another child from an average background.

Many studies have investigated the link between parental social and economic status and that of their children. That a link exists is generally undisputed, although the strength of the link and its causes are more open to question. Part of this link can be attributed to differences in the status of neighbourhoods inhabited by families at different points in a ranking of social and economic advantages. Educated families are more likely to live in educated neighbourhoods. If educated neighbourhoods matter, then having educated parents provides benefits over and above those advantages arising through parents' direct influence. Having said that, we suggest that neighbourhoods are not major contributors to social immobility. Our estimates suggest that at most one tenth of the association between our own education and that of our parents is attributable to the type of neighbourhood in which they chose, or could afford, to live.

Our results relate to children raised in the 1960s and 1970s. Are they still relevant today? We do not have the data to test this fully, but we investigate the issue by comparison of broader area effects on this and a later cohort (teenagers in the 1980s):

- We find no evidence that the link between spatial location and educational attainment declined between the 1970s and 1980s.

One reason to expect a change in the importance of childhood neighbourhood is if educational and income deprivation has become progressively more concentrated in particular neighbourhoods:

- We find no evidence for increasing spatial concentration of educational disadvantage in census wards from 1971 to 1991.

A novel feature of this study is that we also consider the impact on social tenants of living in neighbourhoods with different characteristics. Differences between social tenants in their neighbourhood quality – residents incomes, education or wealth for example – are less related to their own incomes and resources than are differences between property owners' or private tenants' neighbourhoods. This is because social tenants' choices of residential location amongst council homes are less determined by their ability to pay for housing than are the choices of home-buyers and private renters. One view is that relationship we observe between childhood neighbourhood and adult attainments is purely attributable to parental resources, and the fact that more-educated, wealthier families live in more educated, wealthier neighbourhoods. If this were true, we would not expect to find a link between neighbourhood education levels and the eventual qualifications of social tenant children. What we show is that this link exists, suggesting that there are real benefits from living in more educated neighbourhoods, regardless of ones own family background.

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Acknowledgements

Steve Gibbons is a lecturer in Economic Geography in the Department of Geography and Environment at University College London and affiliated to the Centre for the Economics of Education at the Centre for Economic Performance, London School of Economics.

1. Introduction

Does neighbourhood quality affect a child's ultimate educational attainment? This is the central question addressed in this paper. Specifically, we consider whether or not the educational composition of the resident population in a neighbourhood makes a difference to the academic achievements of children who grow up there and focuses on identifying this effect. For sociologists and psychologists, acceptance of the effect of neighbourhoods on behaviour, development and action follows naturally from social and psychological theory. The relevant empirical questions are more along the lines of "how big are the effects" and "through what channels are they mediated". Economists, on the other hand, tend to be sceptical about the very existence of neighbourhood effects on attainments. We are more inclined to attribute apparent associations between neighbourhood and individual outcomes to family-based inputs and geographical sorting of like families, or to local school quality and funding. This study carefully compares the results of various econometric approaches to uncover evidence that neighbourhood does indeed matter, albeit in a relatively small way once we account for family and individual differences, school quality differences, and parental selection of residential neighbourhood.

The results are based on data from the National Child Development Study (NCDS) – the only British dataset which identifies the cohort members' residential location to a neighbourhood level. From this, we can match data on neighbourhood characteristics from the 1971 and 1981 Census to the cohort's residential addresses in childhood and early adulthood. The original NCDS cohort dates from 1958, so any results based on the experience of these children in the 1960s and 1970s have something of a historical flavour. A newer cohort survey, the 1970 British Cohort Study (BCS), has no neighbourhood identifiers nor address postcodes, so is less useful for our purposes. However, we can compare broader area effects and changes in overall intergenerational educational mobility between the NCDS and BCS.

Measurement of neighbourhood effects on individual outcomes is plagued by well-known empirical problems. The most serious issue arises from the sorting of families by resources into areas of differing residential quality, and the potential for like-minded parents to select neighbourhoods and schools on the basis of their anticipated effects on child outcomes. These factors mean that similar families tend to be spatially clustered. Separating contextual neighbourhood influences from the direct effect of family inputs is difficult. Saturating an empirical regression model with parental characteristics is a doomed strategy, since the precise operational neighbourhood group is rarely defined or known, and the relevant neighbourhood characteristic is measured with error. Parental characteristics can be good proxies for neighbourhood characteristics and tend to swamp background variation in measured neighbourhood attributes. Estimates obtained this way will most likely be small or imprecisely measured, since selection by parents on neighbourhood characteristics means that there may be little useful variation in neighbourhood quality, conditional on parental characteristics.

In practice, no single, non-experimental method can provide consistent estimates of the influence of a neighbourhood on a randomly assigned individual. The approach taken in this paper is to compare results from a number of empirical strategies. Firstly it explores the impact of adding and removing key factors in a traditional human capital production function with neighbourhood inputs. Secondly, we test for the presence of school selection bias in the estimates by using local variation in property characteristics to predict neighbourhood quality. This strategy assumes that property characteristics will be unaffected if motivated parents or children converge on good quality schools. Thirdly, we treat social tenants as randomly assigned to neighbourhoods, relative to the selection processes that bias estimates of neighbourhood effects, and estimate the magnitude of effects on children in this group.

Few empirical studies attempt to separate out community influences on individual outcomes from school-based influences and most blur the distinction between peer group effects in the class-room and role model effects from adults. This study shows that the educational status of the community – as measured by the proportion of highly qualified adults – is the strongest available neighbourhood-level predictor of individual educational attainment, from amongst a selection of Census variables of the type commonly used to measure neighbourhood deprivation. Moreover, this educational status variable has an impact on individual attainments over-and-above its potential peer-group-related effects on local school performance. The existence of these non-schooling related effects, and the impact of owner-occupier characteristics on social tenants, is suggestive of role-model effects operating through the formation of expectations based on observation of the local community.

The structure of the paper is as follows: Section 2 briefly reviews the existing literature, to set the work in context. Section 3 describes the estimation strategy in some detail. It starts with a simple linear human capital production function model, and uses this to develop various empirical strategies for identifying a structural neighbourhood effect on attainment. Section 4 describes the data set, sample and variables. Section 5 presents and discusses the empirical results on attainment of adult qualifications, and abilities and aspirations at compulsory school leaving age. Section 6 provides an overview of the implications of area-related effects for intergenerational educational mobility and inequality. Concluding remarks appear in Section 7.

2. Literature and Context

Although there are earlier examples (*e.g.* Datcher, 1982), much of the recent interest in the effect of neighbourhoods on individual's educational and labour market outcomes stems from the work of Wilson (1987). Wilson argued that the increased concentration of poverty and worklessness in inner-city districts in the US has had an adverse effect on the behaviour and development of residents in these neighbourhoods. Wilson sees work, and the expectation of work, as central to a community's discipline, organisation and social cohesion. This idea of this breakdown in the organisation and social relations is often cast in terms of social capital (Coleman, 1988; Coleman, 1994). Social capital extends the ideas of human capital to investments and changes in the systems of relationships in a community that facilitate individual action. In other strands of the literature, neighbourhood influences are explained in terms of Bronfenbrenner's ecological models of child development, in which neighbourhood provides one of numerous contexts for individual development (Bronfenbrenner, 1979). Other approaches, such as Sampson and Byron Groves (1989), refer to Shaw and Mackay's social disorganisation theory (Shaw and Mackay, 1969) in which low economic status, ethnic heterogeneity and residential mobility in the community lead to breakdown in social organisation and consequent crime and delinquency. Although much of the empirical research recognises and refers to these theories, the actual approach is usually ad-hoc, and seeks to find influences from various aspects of neighbourhood socioeconomic status or deprivation on individual outcomes.

This empirical work, and the theoretical discussion of the mechanisms through which these effects are mediated, has been concentrated in the quantitative sociological literature. The range of outcomes analysed is wide: school drop outs, educational attainments, teenage pregnancies, drug and alcohol use, crime victimisation and offences, IQ in infancy, child maltreatment, infant mortality. Researchers' choice of operational neighbourhood or community characteristics shows similar variety: neighbourhood income and poverty, composite socioeconomic status, occupational status, female-headed families, welfare receipt, joblessness, race, social housing, neighbourhood deprivation indices. This extensive literature is summarised in Gephart (1997) and Jencks and Mayer (1990). The majority of the studies use quite small samples on specially selected groups. Most do not focus on identification issues, beyond controlling for an ad-hoc set of parental characteristics.

Directly related to the current work, and using UK data, is Garner and Raudenbush (1991). This study uses data on 2500 young people leaving school from 1984-1986 in one Local Education Authority in Scotland, matched to 1981 Census data. Neighbourhood quality is measured by a deprivation score derived from 12 Census characteristics at enumeration district level. The authors' estimates show that a 90th percentile to 10th percentile change in neighbourhood deprivation relates to a change in attainments equivalent to around two O-level passes. The strength of their data is that the models can include school dummies to control for secondary school effects, plus primary school age test scores, alongside basic indicators of parental background. The disadvantage is that it focuses on one area and is not easily generalised.

Also focussing on educational outcomes, Kremer (1997) estimates that an additional year of mean Census tract education in the US increases individual education by around 0.14 years, but concludes that changes in residential segregation have little impact on inequality and intergenerational mobility. Casting neighbourhood effects in terms of ethnic group effects, Borjas (1992; 1995) finds an impact from mean ethnic group education levels on education years. Jensen and Seltzer (2000) use a small sample of Australian pupils from 1996 and find influences from neighbourhood income, unemployment or educational attainment on intentions to continue in education. Drawing a distinction between immediate and broader neighbourhood impacts, Overman (2000) finds that the proportion in the community with vocational qualifications in the wider neighbourhood increases drop out rates in a sub-sample of the Australian Youth Survey. Community vocational qualifications have a stronger impact than neighbourhood educational qualifications or incomes, but their impact is reversed in smaller micro-neighbourhoods. Duncan (1994) finds significant effects from neighbourhood incomes on white males and more affluent groups, but no effects on disadvantaged groups, similar to Datcher (1982), who finds significant income effects on years of education for whites only. A more extensive body of literature describes the effects of environment on children's behaviours and early attainments, for example Brooks-Gunn, Duncan *et al.* (1993), Chase-Lansdale, Gordon *et al.* (1997), and, for the UK, McCulloch and Joshi (2000) or Gibbons (2001).

Technical discussion of the identification of neighbourhood effects is largely confined to the economics literature. Manski (1993) shows that *endogenous* neighbourhood effects, where the outcome of individuals is dependent on the average of the same outcome in a local reference group, are not, in general, separately identifiable from dependence on unobserved on group characteristics. Nesheim (2001) discusses parametric identification of neighbourhood effects in a model in which the empirical relationship between educational outcomes and local mean neighbourhood schooling attainments is determined by schooling as an input into human capital production, and by parental selection of residential neighbourhood. His approach requires estimation of parents' demand for schooling in a non-linear hedonic price function, and uses the non-linearities in this locational choice equation to provide instruments for neighbourhood quality. The approach adopted in our study is based on similar intuitions, but employs parental demand for property characteristics to predict variation in neighbourhood mean education levels which is exogenous to characteristics of residents in social housing.

Another strand in the literature looks to quasi-experimental evidence on the effect of neighbourhoods, using random re-assignments of families to new neighbourhoods. Evidence from Chicago's Gatreaux Assisted Housing programme indicates that moves from the city to the suburbs reduces drop out rates and improves college enrolment (Rosenbaum, Kulieke *et al.*, 1988; Rosenbaum, 1991). Using data on the Moving to Opportunity programme in Boston, Katz, Kling *et al.* (2001) find short run treatment-on-the-treated effects on behaviour, health and well-being. Although the experimental approach is not subject to the same sources of bias as regression based estimates, it is not easy to identify causal factors or to generalise the results.

3. Models and Empirical Identification Strategies

3.1 A simple model

This section develops a minimal linear specification for estimation of neighbourhood or community effects on education. Standard economic models of human capital development focus on child-level production functions of the type:

$$h^c = h\left(h^p, h^n, z, y, t; b\right) \qquad (1)$$

where h^p represents parent's own human capital, $h^n = E\left[h^p \mid j\right]$ measures neighbourhood or community inputs in area j, z represents school-based inputs, $?$ represents individual innate abilities, t represents time or effort spent in direct parental involvement, and b is a vector parameterising the partial derivatives. A child's school quality depends on the catchment area community inputs h^n, possibly on parent's own financial inputs s (most importantly if the parents decide to send their child to a school in the private sector), and on other factors like aggregate school expenditures and teaching quality inputs m.

$$z = z\left(h^n, m, s; g\right) \qquad (2)$$

Assume that parents first make a choice of *locality* of residence – say a county or city, and its corresponding local education authority – according to labour market opportunities, returns to skills in the local labour market and other exogenous factors. They then decide in which *neighbourhood* to live according to physical property characteristics and local amenities, the quality of local schools and the educational status of neighbouring adults. Since admission to schools in the state sector is generally based on residential location, parents can only choose h^n and m simultaneously with choices over housing and other local amenities. Parents observe all these inputs, but can only vary the inputs to z, other than own expenditure, by changing their spatial location. Imagine that the basis of parental choice of residential location is a family-level utility function with local consumption goods q, human capital attainments of the average child h^c, non-spatially related numeraire consumption good c and family-specific preference parameters q :

$$U = U\left(h^c, q, c; q\right) \tag{3}$$

or, substituting the observable inputs into human capital and schooling:

$$V\left(h^n, m, s, t, q, c; q, b, g, y\right) \tag{4}$$

Neighbourhoods are repositories of three community goods: housing and environmental services q, community educational capital h^n and local school performance z. A location is completely described by $\left(h^n, z, q\right)$ and hence by $\left(h^n, m, q\right)$ if the parameters of the school production function are identical within localities. Neighbourhood property prices are described by a hedonic price function:

$$P = P\left(h^n, m, q\right) \tag{5}$$

where the implicit prices P_h, P_m, and P_q are constant across neighbourhoods (within localities). The budget constraint faced by parents with k children, in the decision on residential location and human capital investments is:

$$w = c + P\left(h^n, m, q\right) + ks + wkt \tag{6}$$

where w is the permanent income stream from lifetime income, or those components of income that are available to finance or guarantee loans for purchase of property or long term expenditures on a child's education. Expenditures c, $P\left(h^n, m, q\right)$, s are permanent streams of lifetime expenditures, and t is the proportion of life spent attending to a child's education. Maximisation of (4) subject to (6) gives the optimal choices of the arguments of the utility function in terms of permanent income (and hence h^p), the implicit prices, family size and demand parameters:

$$x = x\left(h^p, P_x, k; \Phi_x\right) \tag{7}$$

A family chooses a residential location which jointly satisfies their demands for h^n, m, q. The distribution of the demand function parameters (Φ_x) across families will depend on the distribution of parental preferences (q), and their knowledge and expectations of the parameters of their children's human capital production function (b) and school production function (g). Families with a stronger preference for their child's education, or for whom neighbourhood status is more productive (either directly or through school peer groups) will choose higher educational status neighbourhoods[1].

Parental demands for location-based characteristics drive the sorting of individuals into neighbourhoods by income and preferences. Clearly, neighbourhoods that have concentrations of high quality housing stock, or have good local schools will be populated by high wealth, high human capital households, assuming these are normal goods and that capital markets are imperfect. Exogenous variation in characteristics of the neighbourhood which are normal goods generates sorting along educational lines, even if there are no benefits from living in a high education neighbourhood. Parents with high demands h^n, m, and q will populate neighbourhoods with high stocks of these factors, leading to high correlation between the preferences, incomes and education of neighbours.

Using a linearised empirical representation of a simple Cobb-Douglas production function, we have:

$$\ln h_i^c = b_1 \ln h_i^n + b_2 \ln z_i + b_3 \ln h_i^p + b_4 \ln t_i + b_5 \ln y_i + \mathbf{x}_i' \mathrm{b}_6 + e_i \qquad (8)$$

where $\mathbf{x}_i$ is a vector of other locational characteristics. Even if we agreed that this was complete specification, consistent estimation of b_1 in the human capital production function is hindered by the lack of precise empirical counterparts to its inputs and because all the inputs are subject to parental choice. Most efforts at estimating a human capital production function like (8) implicitly exploit substitution of the unobserved factors by linear approximations to their demand functions, or otherwise assume that ad-hoc inclusion of

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[1] An alternative interpretation in a dynamic setting is that the distribution of parameters reflects differences in the discount rate applied by parents to future dynastic earnings or children's human capital in the utility function.

controls is sufficient to guarantee that $E[e_i \mid h_i^n] = 0$. Indeed, this is the first empirical strategy used in this paper.

3.2 Assumptions in alternative specifications

3.2.1 Community or area models

Gephart (1997) refers to versions of (8) without any individual or parental controls as *community* models. A pure community model of educational attainment might maintain that parental inputs have no effects which are independent of the community. A communitarian social philosophy would support this kind of model, where existing community values provide "authoritative horizons" which fix the goals that individuals pursue, and communities define individual identity (Kymlicka, 1990). Sampson and Byron Groves (1989), for example, discuss and test a community-level model based on social disorganisation theory. Community or area-only models restrict b_2 to b_4 in (8) to zero. This is not a structural model in the economic mould, but is appropriate if we believe that parental characteristics are either irrelevant to a child's education, or are completely determined by the characteristics of their community – or if we simply want a description of the data. However, OLS on this equation obviously fails to provide a consistent estimate of b_1 in the structure of equation (8) unless b_2 and b_3 are all structurally zero[2]. This is because family inputs not included in the estimating equation are all correlated with h^n through the common preference parameters and income variables in the demand functions (7). Also, if the demand for neighbourhood status depends on child's abilities, consistent estimation of b_1 requires $b_5 = 0$.[3]

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[2] We may also require $b_4 = 0$, if parental time (or effort) spent on childrens' education is related to their own human capital. With a budget constraint like (6), the loss in income from time and effort spent on a child can cancel out any benefits, so time will be unrelated to income or own education.

[3] Tests of these restrictions in an empirical may just show that our measures of community inputs are imprecisely measured, either because we are measuring the wrong things, measuring the right things badly, or because they are measured at inappropriate levels of geographical aggregation.

A community-based approach does not necessarily rule out separate effects from schools and neighbourhoods. A first generalisation of the community model that avoids including any parental characteristics in the empirical production function – and consequent attenuation of the estimate of b_1 if h^n is measured with error, or parental characteristics are structurally dependent on h^n – removes the restriction on b_2 and allows effects from school quality. As before, consistent estimation of b_1 and b_2 by OLS requires that b_3 to b_5 are all structurally zero. An interpretation of this is that parental preferences, education, incomes and child abilities have an effect on educational outcomes, but only via the demand for schooling. In this case the human capital and school production functions form a recursive structure.

3.2.2 Community, schooling and parental background

Neighbourhood models which allow for parental background or individual effects are called *contextual* in the sociological literature. In principle, these are just reduced form versions of (8). If we substitute parental characteristics for the demand for school quality, we get a reduced form human capital production function in neighbourhood and family background and individual characteristics only, with other area controls $\mathbf{x}_i$:

$$\ln h_i^c = (b_1 + b_2 g_1) \ln h_i^n + \mathbf{f}_i' \tilde{\boldsymbol{\beta}} + \mathbf{x}_i' b_6 + w_i \tag{9}$$

The vector $\mathbf{f}_i$ must include individual abilities, parental education, number of children and proxies for permanent incomes and preferences. Estimation of (9) gives a consistent estimate of the sum of the effects of neighbourhood on human capital production operating through peer-group effects at school ($b_2 g_1$) and directly through other channels (b_1).[4]

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[4] A complication arises if school funding is dependent on local taxes, or otherwise on local wealth and human capital, since now school performance depends directly on h^n through peer group effects, but also indirectly via expenditures on the school. In this case, estimation of (9) does not identify neighbourhood human capital externalities separately from effects of neighbourhood human capital on school funding. We must include controls for school expenditures if these vary within localities, or control for school quality directly. In the

With data on a child's school quality, we can enter z directly. If parental human capital, incomes and child abilities are measurable, we need only substitute for unobserved parental time or dedication to a child's schooling. We shall assume that this depends on parental preferences for their child's education and the number of children in the family that we include in $\mathbf{f}_i$. The empirical production function is now:

$$\ln h_i^c = b_1 \ln h_i^n + b_2 \ln z_i + \mathbf{f}_i' \tilde{\mathbf{ß}} + \mathbf{x}_i' \mathrm{b}_6 + w_{2i} \tag{10}$$

Clearly this is a restrictive specification. More realistically, the marginal product of neighbourhood and schooling in the human capital production function could depend on observable characteristics – ability as measured by early test scores, parental skills, education or other demographics. We might also believe that the effects of neighbourhood or community are mediated via family characteristics, for example if children only benefit from highly educated neighbours if their parents are educated enough to engage socially with the community. In these cases we may prefer an empirical specification with neighbourhood-family interaction terms:

$$\ln h_i^c = b_1 \ln h_i^n + b_2 \ln z_i + 1_1'\left(\ln h_i^n \cdot \mathbf{d}_i\right) + 1_2'\left(\ln z_i \cdot \mathbf{d}_i\right) + \mathbf{f}_i' \tilde{\mathbf{ß}} + \mathbf{x}_i' \mathrm{b}_6 + w_{3i} \tag{11}$$

Here, $\mathbf{d}_i$ is a vector of indicators of parental or individual type, b_1 and b_2 measure the effects of neighbourhood and schooling on the baseline group, and $\mathbf{?}_1$ and $\mathbf{?}_2$ reflect heterogeneity in the returns across parental or individual types. Rejection of $\mathbf{?}_1 = 0$ and $\mathbf{?}_2 = 0$ supports selection on neighbourhood and schooling by observable characteristics, and implies heterogeneous marginal products across groups.

British setting, funding formulae for state school expenditures ensure that they are almost constant within Local Education Authorities, so fixed effects at this level are sufficient.

3.3 School-quality selection

3.3.1 Checks using school characteristics and child abilities

Clearly, unless we treat a model such as (10) as a complete specification, or otherwise assume that the unobservables are conditionally independent of neighbourhood quality, then estimation by ordinary least squares regression will not consistently estimate the structural parameter of interest, b_1. Unobserved components of individual ability that are observed by the parent, child or school will generate selection bias in the estimates of b_1 and b_2. This occurs if the demand for neighbourhood status and school quality, and the production of human capital, is dependent on unobserved ability. However, for current purposes, all we really want is a consistent estimate of b_1.

It is straightforward to assess the extent to which school selection effects bias our estimates of the key parameter of interest, b_1, by using data on school performance, some observable school characteristics, and any measure of individual ability. The most likely scenario is that there are ability selection effects on schooling, with high ability children attending better schools, or high-motivation parents pushing hard for admission to good schools. In this case, b_2 will be an upward biased estimate of the structural effect of school quality. Positive correlation between h^n and z implies that OLS estimates of b_1 will be inconsistent. Even without selection, b_1 will be inconsistent if z is a noisy measure of school quality, since the estimated neighbourhood parameter may pick up unobserved components of school quality. A simple check is to include additional school characteristics which are proxies for m in (2). Change in the estimate of b_1 would suggest that unobserved school quality and selection effects are influencing the measured direct neighbourhood effect. A further check is available, since we can compare the estimate of b_1 in (10) with and without exclusion restrictions on parental preference variables or controls for child abilities. Although these are not rigorous tests, the range of variation in estimates of b_1 under different specifications can be informative.

3.3.2 Identification using exogenous local characteristics

The structure outlined above suggests another approach to identifying the neighbourhood parameter b_1, separately from unobserved school quality selection effects. The demand for housing services, or local amenities (q) implies an equilibrium relationship between average local wealth and the average quantity of q in the neighbourhood. Since average local wealth depends on average local education or human capital, we can write mean neighbourhood human capital as a function of q. Mean neighbourhood human capital will also depend exogenously on the proportion of households in social housing, since (almost by definition) households in social housing have lower incomes and lower educational attainments on average than owner-occupiers and private tenants. The neighbourhood mean human capital generating function is:

$$\ln h_i^n = h^n\left(q_i, p_i, z_i\right) \tag{12}$$

Estimation of (10) by instrumental variables, using neighbourhood property characteristics q and the proportion of social housing p as instruments, gives a consistent estimate of b_1 even if there are unobserved school quality components m, under the assumption that $E[m|q]=0$ and $E[m|p]=0$. This requires that unobserved school quality factors do not depend on local property characteristics or the proportion of social housing, conditional on localities defined by $\mathbf{x}$ and other controls in (10).

3.4 Social tenants and parental selection

Focussing on neighbourhood as a factor in the human capital production function, we can re-write our human capital production function as:

$$\ln h_i^c = b_1 \ln h_f^n + \mathbf{x}_{if}'\mathbf{a} + h_f + e_i \tag{13}$$

where h_i^c is the attainment of a child i in family f, $\mathbf{x}_{if}$ is a vector of observed individual and family characteristics, h_f is an unobserved family specific effect, and e_i is an individual specific error term. As discussed in Section 3.1, the potential problem in estimation of (13) is that the neighbourhood characteristic h_f^n is correlated with unobserved or badly measured characteristics of the families under observation. This correlation arises principally through the demand for community status, school quality, property characteristics, environmental characteristics and other local amenities, which leads to a dispersion of land rents and property prices across geographical space. This dispersion in land rents and property prices generates dispersion in family incomes, wealth and hence education across neighbourhoods.

We are interested here in the relationship between neighbourhood educational composition and the attainments of children. The relationship between the education of a parent in the sample, and the mean education in the neighbourhood can be written:

$$h_f^p = h_f^n + w_f \tag{14}$$

The regression coefficient in the regression of parental h_f^p on neighbourhood mean is one[5]. Running an OLS regression on a cross-section in (13) gives unbiased estimates of the parameter b_1, only if the parental characteristics are measured without error, and the unobserved family effects are uncorrelated with the neighbourhood measure or with other family characteristics. This is true even if households are randomly assigned to neighbourhoods.

However, assume we have two samples of individuals, the first group s randomly allocated to neighbourhoods, the second group o systematically sorted into neighbourhoods by education. We have the overall mean education in each neighbourhood, after assignment. From this we could infer the effect of neighbourhood composition on the randomly allocated group by regression of our outcome variable on neighbourhood composition without any parental controls. To formalise this, assume we have in each neighbourhood, proportion p families, who sort themselves into neighbourhoods on the basis of individual demands for some neighbourhood amenity q. Assume we have another group of $(1-p)$ families who are

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[5] The neighbourhood mean is $h_f^n = \frac{1}{J}\sum_{f=1}^{f=J} h_f^p$. The correlation coefficient between parental education and neighbourhood mean education is $r_h = s_n^2\left(s_n\sqrt{s_n^2 + s_w^2}\right)^{-1}$.

allocated to neighbourhoods in a random way, or in such a way that their characteristics are uncorrelated with the neighbourhood amenity. The sorting processes relating individual characteristics to the neighbourhood can be written as:

$$h_f^s = m^{hs} + z_f^s, \qquad h_f^o = m^{ho} + fq^n + z_f^o \tag{15}$$

$$h_f^s = m^{hs} + x_f^s, \qquad h_f^o = m^{ho} + yq^n + x_f^o \tag{16}$$

The m are constants and f and y are parameters. The expected value of education in any neighbourhood n is then, from (15):

$$E[h_f \mid n] = pm^{ho} + pfq^n + (1-p)m^{so} \tag{17}$$

The covariance of the family and mean neighbourhood education for each group is:

$$Cov(h^s, h^n) = 0, \qquad Cov(h^o, h^n) = pf^2 \cdot Var(q^n) \tag{18}$$

and the covariance of the unobserved family characteristic and the neighbourhood measure is:

$$Cov(h^s, h^n) = 0, \qquad Cov(h^o, h^n) = pyf \cdot Var(q^n) \tag{19}$$

Under these assumptions, we can identify the effect of h^n on individuals in the s group without controlling for h_f^s. If the sample used to construct the neighbourhood mean is sufficiently large, then the sample mean of h_f^s is the same in all neighbourhoods, so does not contribute to variation in h^n between neighbourhoods. This may be a strong assumption, since any sampling variation will mean the first conditions in (18) and (19) will not hold exactly. However, provided $Cov(h^o, h^n)$ is large, so $Var(h^n)$ is large, the regression coefficient derived from $Cov(h^s, h^n)/Var(h^n)$, or $Cov(h^s, h^n)/Var(h^n)$ will be near zero, so the bias in the OLS estimate of b_1 is negligible. Moreover, from (16), if we observe neighbourhood characteristics or local housing characteristics q^n which have value for group *o* only, we can use these as instruments for $h^n = E[h_f \mid n]$ in an equation (13) estimated on group *s* only.

It is a plausible, though contentious, assumption that council tenants are randomly allocated to their neighbourhood. This will be true to the extent that the neighbourhood *location* of an allocated council home is largely unrelated to the resources and preferences of the tenant. Under this assumption, council tenants provide a suitable group s for the strategy described above. If a link between council tenants education and that of their neighbours' is attributable to a council policy of matching tenants, or parents' desire to be housed amongst similar tenants, then the characteristics of owner occupiers in the neighbourhood will provide good instruments for the neighbourhood status of council tenants.

3.5 Local non-linearities in the neighbourhood effect

Local non-linearities in the relationship between neighbourhood and educational outcomes have implications for the long-run impact of neighbourhood on intergenerational mobility and inequality. A linear relationship with moderate slope suggests that the neighbourhood-educational process is mean reverting. If there are local non-linearities in the relationship, such as the threshold or contagion effects highlighted in Crane (1991), then there may be non-linearities in the familial intergenerational relationship. This can mean that neighbourhoods or dynasties from one end of the distribution of neighbourhood quality, may remain permanently separated from those at the other end (see Loury, 1977; Benabou, 1996; or Ioannides, 1997 for example). A generalisation of the empirical specification (10) that allows for general nonlinearities in h_i^n is:

$$h_i^c = g\left(h_i^n\right) + \tilde{\boldsymbol{\beta}}'\mathbf{f}_i + w_i \qquad (20)$$

This can be estimated by semi-parametric methods, such as the partial linear model (see Robinson, 1988 for example). An estimate of $\tilde{\beta}$ is obtained as:

$$\hat{\beta} = \sum_i \left(\tilde{\mathbf{f}}_i \tilde{\mathbf{f}}_i'\right)^{-1} \cdot \sum_i \tilde{\mathbf{f}}_i \tilde{h}_i^c \qquad (21)$$

where

$$\tilde{\mathbf{f}}_i = \mathbf{f}_i - \mathbf{m}_b\left(\mathbf{f}_i \mid h_i^n\right) \tag{22}$$

$$\tilde{h}_i^c = h_i^c - \mathrm{m}_b\left(h_i^c \mid h_i^n\right) \tag{23}$$

and $\hat{m}_b(\cdot)$ is an estimate of the conditional mean obtained by kernel regression. An estimate of the function $g\left(h_i^n\right)$ is then obtained by a second stage kernel regression of $h_i^c - \hat{\mathrm{b}}'\mathbf{f}_i$ on h_i^n, at preset sequence of points $\left\{h_c^n\right\}$ using the Nadaraya-Watson estimator.

4. Description of the Data

4.1 The NCDS and Census data sets

Our empirical methods use the framework described in Section 3 to investigate the effects of mean neighbourhood education levels on educational attainments. The data is the British National Child Development Study (NCDS), the only British, individual level data set that contains any information on childhood neighbourhood. This study follows the British cohort born between 3rd and 9th of March 1958, with follow-up surveys at age 7 (1965), age 11 (1969), age 16 (1974), age 23 (1981), and age 33 (1991). A further sweep is underway for 2001. The NCDS has been exploited in innumerable research papers in many disciplines. Census ward identifiers for cohort member's residential addresses are available for 1974 (and 1981), allowing us to match in British Census data from 1971 to 1974. Some Census data is already included in the NCDS files, though for 1974 this is all at enumeration district (ED) and local authority (LA) level, and does not include neighbourhood education. Measures of neighbourhood education and other characteristics at the intermediate ward level must be spliced in from the publicly available ward-level Census statistics.

The ED is the smallest unit for which Census statistics are available. It is the 'input' geographical unit of the Census. Around 10 EDs make up a Census ward. In 1971 there were around 18000 wards, with mean populations of around 3000. The distribution is, however, highly skewed with 50% of wards containing less than 1000 persons. One quarter have more than 4000 residents. The sample of Wards matched to the NCDS sample over-represents higher population Wards (unsurprisingly given the distribution of births), with median populations of about 8000. The number of wards represented in the base NCDS sample used in this study is 5479. Enumeration districts are intended to encompass as many households as the Census Enumerator could cover on the Census day. Whilst they are probably ideal as a neighbourhood measure, some of the most useful Census data is based on a 10% sample, so ED sample sizes are extremely low[6]. We will use mostly Ward-level neighbourhood data. An exception here is an indicator of residence on or near a local authority estate, constructed from the ED-level data in the NCDS. Labour market controls are taken at Local Authority level, plus dummy variables for up to 64 counties of residence in 1974.

4.2 Description of the samples

Estimation of the models is based on samples of men and women from the 1991 NCDS sweep at age 33 who reported their highest educational qualifications. Parental characteristics for these adults come from the earlier childhood sweeps, along with information on their early abilities (age-7 test scores) and the performance and characteristics of the secondary school they attended at age 16. Attrition is a problem in the NCDS. Where possible, parental characteristics are those measured in 1974, but the latest information available from earlier sweeps replaces missing data to maintain sample sizes.[7] All observations without ward identifiers in 1974, or without adult qualification data are dropped. This gives us a maximal sample size of 4538 men and 4835 women. The sample size of each is reduced by around 900 once we drop observations without secondary school quality measures. A similar base sample is used to look at the earlier attainments of the NCDS cohort, focussing on the results of reading and maths tests carried out at age 16.

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[6] The issue of the correct choice of neighbourhood group arises frequently in the literature. Overman (2000) finds differing effects on high school drop out rates from occupational status operating at small and large neighbourhood definitions. Since we have no choice, we use wards. Experimenting on proxies for education, e.g. professional workers, at ED and ward level shows that using either ward or ED, unconditional on the other, gives similar results. Apparently, the choice is not so critical.

[7] This never amounts to more than 5% of the responses for which residential address information is available.

4.3 Description of the variables

All the variables used in the results are defined in Appendix A. Our key regressor is the empirical counterpart to neighbourhood human capital h^n. Potential choices are social class variables, or the educational attainments of adults in the neighbourhood, or some composite of the two. We will focus on educational status only, since this seems the most natural choice in models of educational outcomes. The variable is the proportion of over-18s in each ward with Ordinary National Diplomas, A-levels, Higher National Diplomas, degrees, higher degrees, professional qualifications or equivalent qualifications. Using this, we can readily evaluate the impact of the proportion of adult neighbours with these qualifications on the probability of a child attaining the same qualifications. Models of influences on teenage abilities use the natural log of the age-16 test scores as the dependent variable.

5. Empirical Results and Discussion

5.1 Community and area models

Table 1 shows marginal effects and t-statistics based on ordered probit estimation of the community model of 0, for boys only. Control variables are a selection of key economic, community and geographical characteristics measured at ward or local authority level, with county dummies. The results in row 1 show what happens to children from similar neighbourhoods that differ in respect of the qualifications of residents. Looking at the results in column I, Table 1, it is clear that better educated men originated from high-education neighbourhoods. Better neighbourhood education is the most important of the factors identified here: a one percentage point increase in the proportion of neighbours with A-levels or higher is associated with a 0.67% increase in the probability of a man having at least A-levels by age 33, and a 0.50% decrease in the probability of failing to gain any decent qualifications. These translate into elasticities at the sample mean of 0.23 and –0.31 respectively. Boys from the top decile of educated neighbourhoods (21.7% with A-levels+) were twelve percentage points more likely than those from the bottom decile (3.7%) to end up at age 33 with high qualifications (41% against 27%), but were nine percentage points less likely to end up with no or few qualifications (15% against 24%).

Comparable results for girls are shown in Appendix B, Table 10. Most of what was said for boys in terms of the effect of their origin in the distribution of neighbourhoods applies to girls.

We get similar results if we replace the dependent variable with cumulative time in education. The elasticities on ward education come out at 0.26 for men and women (t = 6.5). The within-county R^2 s from these regressions imply that a maximum of 8% of the variation in time in education is associated with these neighbourhood attributes. Much of this will be attributable to parental background, not community effects. The explanatory role of neighbourhood in educational outcome would appear to be small, relative to other factors.

Even if we reject the community-only model of attainments, these results are interesting since they highlight the important associations between area characteristics and adult educational outcomes. *A priori*, we would expect fairly strong associations unconditional on parents characteristics, because neighbourhood characteristics reflect the characteristics of the individuals' parents. From a policy point of view, these results are useful if we want an area basis for targeting resources to the educationally disadvantaged.

Our second set of results, column II in Table 1, repeats the analysis holding constant the quality of local schooling – specifically the proportion of own-sex 15 year olds studying for GCE O-Levels at the school attended by the child at age 16. Once we take account of the quality of secondary school attended, the effect of neighbourhood education falls by over one third to give elasticities of 0.14 on A-levels and −0.21 on low qualifications. The coefficient is still highly significant, and substantial considering we are only capturing effects over and above anything influencing the measured quality of the child's' schooling at age 16. Even conditional on this measure of secondary school quality, teenagers in the top educational decile of neighbourhoods are 7.5 percentage points more likely to end up with high qualifications than those at the bottom decile, and 5.6 percentage points less likely to end up with the lowest qualifications. Results for women in Appendix B, Table 10, show a similar pattern.

Comparable within-county regressions for time in education tell us that around 20% of the variation in education of men, and 21% for women, is attributable to secondary school quality and neighbourhood together. School quality alone accounts for about two-thirds of this, leaving components of neighbourhood unrelated to school quality to explain around 6% of the variation in time in education.

5.2 Community, area and parental background

5.2.1 Conditional or contextual effects

Table 2, changes the analysis to look at the impact on boys of our measure of neighbours' educational qualifications, conditional on the characteristics of the cohort members' parents and family. The choice of family characteristics included is in line with the basic human capital production function model presented in equation (9), and might be called *contextual*. The specification includes additional geographic controls for urban and high population wards, and high social housing enumeration districts, alongside local labour market measures and sixty county dummy variables. Other neighbour characteristics are excluded[8]. This focuses attention on the relationship between comparable outcome and neighbourhood characteristics – the educational attainments of the cohort member and those of his neighbours during childhood.

The marginal effect of neighbourhood in column I, conditional on parental characteristics, is substantially lower than in Table 1. Most of the coefficients on parental characteristics are significant. Early test scores are highly significant and powerful predictors of attainments, as is well known from other studies *e.g.* Feinstein and Symons (1999). Area characteristics, other than the county dummies and local unemployment rates have little effect. The coefficient on neighbourhood educational status corresponds to elasticities of +0.095/-0.13 on the high and low qualification categories – evaluated at mean neighbourhood education. A boy from the top decile of neighbourhoods is around five percentage points more likely to qualify with A-levels or higher than a boy from the bottom decile – holding constant the characteristics of his parents. Another way of looking at this is that a move from the bottom decile to the top decile of neighbourhoods has an effect on educational attainments of similar magnitude to an extra 2 years of parental education.

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[8] Proportion of in professional occupations and average dwelling size attract negative statistically insignificant coefficients in qualifications or educational years models.

Again, repeating the analysis on time in education gives an elasticity of 0.095 at mean non-compulsory years of education (the *t* statistic is 3.66). The partial R^2 for our ward human capital variable is 0.0024, against an overall within-county R^2 of 0.3008. It is worth noting that, by this calculation, only 0.8% of the variation of time in education attributable to childhood background is explained by teenage neighbourhood educational status!

5.2.2 Investigating school selection

As discussed in Section 3.3, the measured neighbourhood effect could be entirely attributable to school selection by parents and children, where the factors which drive selection are unobserved, and school quality has an effect on individual achievements. If these attributes are correlated with parental education they will also be correlated with the education of neighbours. Selection on schools by parents and children of unobservably different types (or selection on parents and unobserved pupil ability by schools) will lead to inconsistent estimates.

If we believe the simple model of Section 3.2.1, and we trust that the data provides good measures of parental characteristics, then selection on school quality is not an issue. Of course, this strategy alone is unconvincing. Hence, columns II and III indirectly test the assumption that there are no omitted variables which are correlated with neighbourhood education levels and with the quality of local schooling. Firstly column II, includes the measure of local schooling quality as a regressor. We should expect a fall in the neighbourhood effect, because part of the influence of the educational status of the neighbourhood will operate through peer group effects in school. Column A estimates school ($b_1 + b_2 g_1$) in equation (9), whereas column II estimates (b_1). In fact, the size of the estimated impact of neighbourhood is reduced by only around 20%, and remains significant at the 1% level. Around 20% of the neighbourhood effect could be attributable to selection on schooling or school peer-group effects, but the higher estimate is only one and a half standard errors above the lower point estimate. The marginal effects of school quality and neighbourhood are similar, but the elasticities at the mean suggest that relative improvements in the quality of school attended are twice as important as changes in neighbourhood quality in terms of educational outcomes. This finding of the importance of neighbourhood factors over and above secondary schooling is in line with Garner and Raudenbush (1991).

Certainly, the proportion of boys studying for GCE-O levels is a crude quality measure – though not unlike the performance measures used in the school league tables of the last decade. It could be argued that the neighbourhood effect is merely picking up residual, unobserved characteristics of local secondary schooling. Secondly, if there is selection bias on school quality then the estimate of entire parameter vector is inconsistent. To assess how far this affects our main parameter of interest, column III adds in dummy variables for school type. We would expect attenuation of the estimated coefficients on any variables which are correlated with previously unobserved differences in school performance across school type categories. Indeed the estimated coefficient on the school quality variables is nearly halved, yet the estimated neighbourhood effect is almost unchanged and the t-statistic is increased slightly. We can interpret this as showing that there are no important unobserved components of school quality which affect adult attainments and are correlated with levels of education in the neighbourhood. This suggests that selection on school characteristics does not bias the estimate of the influence of neighbourhood status[9]. Results for girls are shown in Appendix B.

5.2.3 Robustness to changes in specification

Table 3, rows 1-3 show that estimates are not unduly sensitive to the inclusion of additional paternal and maternal characteristics – income, social class and socioeconomic group, where these are available. The estimates on the neighbourhood effect coefficients are statistically comparable to those in the original models, and are significant to at least the 5% level. In the worst case, including 32 socioeconomic group dummies attenuates the coefficient by over 25%, but then current parental employment skill group is not predetermined and is potentially endogenous in a model of neighbourhood human capital formation. Row 4 checks the sensitivity to exclusion of parental interest dummies – which are also potentially endogenous. A community where parents are visibly supportive of their children's schooling may encourage this behaviour in its constituents. These are, however, the best proxies available

[9] There may be unobserved effects from primary school quality, which are not captured by secondary school performance. However, it seems fairly implausible that age-16 residential neighbourhood is a better proxy for an individual's primary school quality than it is for secondary school performance.

for parental qualities that motivate selection on higher-education neighbourhoods – those with high interest in their child's education will be those that seek out the returns to good neighbourhoods. Nevertheless, removing these controls pushes the coefficient on neighbourhood up by less than 25%. Row 5 shows the impact from removing the age-7 academic ability controls from the model with parental background and schooling. Removing the age-7 ability controls increases the coefficient by only 10%. Adding in an age-11 reading test score decreases the coefficient by around 10%. Given these figures, it is unlikely that selection on unobserved individual abilities accounts for a substantial proportion of the estimated neighbourhood effect. Section 5.4 investigates these issues further.

5.2.4 Heterogeneity in returns

Estimation of the model of equation (11) allows us to investigate heterogeneity in returns across groups. Using median or quartile dummies for age-7 test scores in the vector $\mathbf{d_i}$, we find that the educational benefits of neither neighbourhood nor school quality differ across ability groups. Using quartile dummies, the tests of the interaction terms on neighbourhood give $c_3^2 = 1.16$ (*p*-value = 0.68), and on school performance $c_3^2 = 2.69$ (*p*-value = 0.44). The average marginal effect of neighbourhood is –0.19/+0.26 and on school performance –0.11/+0.14. On the basis of this evidence it seems that concerns about ability selection effects, or complementarities between neighbourhood and ability are unfounded, unless selection is on components of ability which are unrelated to early test scores.

Allowing for interaction terms between parental interest dummies and neighbourhood and parental interest and schooling gives an indication of how the benefits of neighbourhood and school quality vary across parental interest groups. Here, there *is* evidence that parental interest affects the returns to neighbourhood or school performance in the human capital production function, or that the returns affect parental interest – these are observationally equivalent. The interaction terms are significant for both neighbourhood ($c_{11}^2 = 19.7$ *p*-value = 0.05) and school performance ($c_{11}^2 = 22.8$, *p*-value = 0.02). Allowing for this heterogeneity, the marginal effect of neighbourhood in the modal group is –0.27/+0.37, but ranges from +0.45/-0.20 for those who expressed little interest and did not read to their child, up to –0.75/+1.01.

Estimation of (11) using parental education dummies provides little evidence of important heterogeneity across parental education groups. Interaction terms between neighbourhood education and an indicator that the father stayed on after minimum school leaving age, or that mean parental years of education exceed 15, give positive but insignificant estimates of the interaction coefficient. The main effects of neighbourhood and education remain significant. This is in line with the non-parametric estimates of the relationship between adult educational attainments and parental-neighbourhood education, presented later in Section 6.1.2.

5.3 Predicting neighbourhood status from housing type

Section 3.3.2 suggested that property characteristics and the proportion in social housing provide suitable instruments for neighbourhood status, if we want to purge our estimates of school selection effects. These neighbourhood characteristics are unchanged by parental selection on school quality, at least in the short run.

Using 100% Census sample variables as instruments also corrects for sampling variation in the 10% sample Census data. A potential drawback with the Census data from the 10% sample is the sampling error when analysing at low levels of disaggregation. The results from comparison of the 100% and 10% samples in the full Census sample are worrying: regression of comparable employment rates from the 100% sample on the 10% sample gives a coefficient of 0.348, implying that some 65% of the sample variance in employment rates is noise! Fortunately, the NCDS matched sub-sample is biased toward higher population wards. Repeating on this sample gives a regression coefficient of 0.83. Some 17% of the sample variation may attributable to sampling error.[10] Assuming these

[10] The maximum variance attributable to measurement error in the education variable can be derived, for a given sample size. The underlying qualifications variable is dichotomous and the maximum standard error of the mean in a ward occurs when all the true variance is within-ward. Since the proportion of the population with A levels or degrees in 1971 was 0.114, the maximum variance within-ward is 0.101. Based on samples of only 75 over-18s (the median in the Census), the ratio of the square of the standard error of the mean to the actual variance in the data is around 0.22. By this calculation, at most, 22% of the variance is noise. Regression of 100% on 10% derived measures of unemployment rates and employee/total employment ratios from the 1991 Census also suggests that the ward-level 10% samples give estimates that are 20% down on their true value.

figures are correct, we would expect any regression coefficients on this to be downward biased by at least 17%. Additional correlated variables in the regression will attenuate the coefficient further.

Table 4 shows 2-step instrumental variables estimates with a first stage linear regression and second stage ordered probit as in Table 2. Instruments are the ward-proportions of local authority tenants, and property size[11], which we may assume are uncorrelated with educational attainments, conditional on neighbourhood educational status, parental property size and tenancy group. An LM test does not reject the overidentifying restrictions on neighbourhood local authority housing and house size in the second step equation. At the same time, these instruments are highly significant in the first step equation (P<0.001). Standard errors in Table 4 are corrected using the method of Murphy and Topel (1985).

Using this method, the point estimates of the marginal effect of neighbourhood on male educational attainments are substantially *higher* – by around 20%. This is roughly in line with the assessment of the amount of measurement error in the 10% sample relative to the 100% sample. The estimates may also be slightly higher because the instruments are better predictors of long-run neighbourhood status than the education variable, so estimates are purged of transient variation in educational status on the night of the Census.

Based on these figures, a family moving from a neighbourhood at the bottom decile of qualifications to a neighbourhood at the top decile would increase the probability of their children gaining these qualifications by over six percentage points, unconditional on neighbourhood schools (31.7% versus 37.8%). The elasticity for the probability of attaining high qualifications with respect to the neighbourhood proportion with high qualifications is 0.11 at the sample mean. The comparable elasticity for failure to gain anything above CSE grade 2 is about –0.15. Continuing the assessment of school quality effects, we see, in moving from column I to column II, that school selection probably accounts for little more 14% of the neighbourhood coefficient. Controlling for observed school quality and type gives an neighbourhood elasticity of high educational attainment of +0.10/-0.14 at the mean, for boys.

[11] More than seven rooms.

5.4 Social tenants' attainments: a randomly allocated group?

We turn now to the method outlined in Section 3.4 using families who were reported as council tenants in both 1969 and 1974. Our assumption is that the neighbourhood status of any socially housed tenant is unrelated to their family resources – *relative to other socially housed children* – and that most of the variation in their neighbourhood status is driven by the proportion of social tenants and the status of neighbouring owner occupiers. Table 5 shows the marginal effects from ordered probit regressions for a pooled sample of men and women. In column I, which includes area, labour market and county controls, we see measured effects of similar magnitude to those obtained using the full sample with parental controls. A one percentage point shift in the proportion of neighbours with A Levels and above increases the probability of the child of a council tenant gaining A Levels by 0.25%. This is equivalent to an elasticity at the mean of around 0.13. The same shift in neighbourhood status lowers the chance of ending up without any formal qualifications by 0.34%. Again, the elasticity is around 0.1. A 10^{th} percentile to 90^{th} percentile move through the population distribution of neighbourhoods would increase the probability of a social tenant gaining A-levels from to 15.6% to 20.1%.

As before, we can assess whether this relationship is mediated through the school environment or elsewhere through social interactions in the neighbourhood, and allow for observable school selection. One argument is that the observed correlation between council tenants children's attainments and the characteristics of home owners in the child's neighbourhood is simply the result of variation in school quality across neighbourhoods – high ability children of council tenants gain places at selective local secondary schools which also attract highly educated owner occupiers into the school catchment area. Including our measure of secondary school quality and mean early test scores attenuates the measured neighbourhood effect by about 30%, but the coefficient is still substantial and significant. The elasticity of the attainment of high qualifications with respect to neighbourhood educational status is still around 0.1, compared to an elasticity of 0.18 with respect to the quality of school attended. Apparently, living in a higher status neighbourhood with average secondary schools was just over half as effective for children of social tenants as going to a better school in an average neighbourhood. As in Table 2, the attenuation of the neighbourhood parameter when schooling is included in the regression can be explained by catchment area peer group effects on school performance.

So far in this section, we have used raw neighbourhood and school quality. Our identifying assumption here was that the allocation of council tenants to neighbourhoods is unrelated to the tenants' own education, incomes, or concern for their child's education. A basic test of the validity of this assumption is to regress parent's education on neighbourhood educational status (with local and county controls). This test suggests that the education of council tenants was not completely unrelated to the neighbourhood in the 1970s. The elasticity between parents' mean years of education and the ward-proportion of adults with A-levels and above is around 0.004 (s.e. 0.0015, N = 2818) for council tenants. This could mean that local authorities matched tenants in terms of their education or incomes, or that better educated tenants pushed for accommodation in better neighbourhoods. Alternatively, the correlation may reflect effects from neighbourhood persisting from the previous generation. Nevertheless, the correlation is weak compared to that for home-owners: the elasticity between home owners' education and neighbourhood status is over ten times higher than that for council tenants, at 0.041 (s.e. 0.002). If all the neighbourhood effect was attributable to correlation with parents' education, then the estimated neighbourhood elasticity of educational outcomes for a home owner's child will be higher by the same factor. In fact, the equivalent elasticity for non-council tenants is only twice that for council tenants (see Table 12, Appendix C).

Even if there is some correlation between parental characteristics and neighbourhood within the socially housed group, it is unlikely that these characteristics are correlated with their non-socially housed neighbours. Again from the discussion in Section 3.4, we can use home-owner characteristics as instruments for social tenants neighbourhood. Table 5, columns II and III present 2-step IV models for social tenants, using home-owner property size and housing amenities as instruments. The overidentifying restrictions test as acceptable using an LM test (p-value=0.352). More direct evidence that supports the use of home owner's characteristics as instruments, is that the instruments are uncorrelated with council tenant's parental education, which we know affects their children's attainments. The F-statistic for the joint test of the coefficients on the five instruments in regression of log mean parental education on these, and the other characteristics in Table 5 is 0.63, with a *p*-value of 0.68.

As with the full sample results, the IV estimates are substantially higher – in fact more than double the estimates obtained using the raw neighbourhood variable. The implied elasticities at the mean are 0.260 on attaining A-levels plus, –0.197 on less than CSE grade 1.

This change is more than we would expect after correcting for sampling variation alone, and suggests that other factors are at work. One possible hypothesis is that it is the educational status of owner occupiers at the boundary between areas of social and non-social that matters for social tenants' educational outcomes. This would be consistent with the existence of role-model or expectations-related effects on human capital accumulation. In this case, the education of neighbouring home-owners may be a better measure of the relevant neighbourhood group than overall ward-level averages. Variation in the neighbourhood attributable to variation in the education of non-socially housed residents results in variation at the social–non-social housing boundary, whereas variation in the relative proportions of social and non-social tenants does not. This view has some further empirical support: including the ward-proportion in social housing in the instrument set reduces the estimated marginal effects to the values obtained with the raw neighbourhood measure. A comparable interpretation is that the IV estimates are, what the programme evaluation literature describes as, Local Average Treatment Effects (LATE) – see Angrist and Imbens (1994). If the structural parameter varies across individuals, or changes over the distribution of neighbourhoods, then the LATE parameter estimate is interpretable as the average effect over the range predicted by the instruments, or for the sub-group affected by variation in the instruments.

As before, we can test the robustness of these results using school quality measures. If the assumption of exogeneity of home-owner property characteristics is correct, we should expect little change. Comparing column III of Table 5 with column IV, which includes a predicted school quality measure[12], confirms our expectations. The measured impact of neighbourhood is almost unchanged[13 14].

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[12] School performance is predicted from school type, and pupil teacher ratio. This separates catchment area effects from school quality effects, and generates a measure of non-transient school quality. Using raw school characteristics or school quality does not change the key result. Entering school quality directly gives a lower coefficient (0.14) on school quality.

[13] The literature on school resources and individual attainments questions the exogeniety of school performance and related characteristics, such as pupil-teacher ratios and school types. Selection into school types will occur according to ability, so the measured association between school characteristics and individual attainments merely shows the clustering of high ability children in certain schools. As the impact of school characteristics is

5.5 Investigating local non-linearities

The parametric approach of the previous results restricts the functional form of the empirical attainment-neighbourhood relationship. Figures 1 toFigure 3 enrich the analysis using the semi-parametric procedure of Section 3.5, by allowing for general non-linearities. Figure 1 shows how the probability of attaining A-levels or higher qualifications by age 33 increases as the educational status of a teenager's neighbourhood increases. Here we see that the likelihood of becoming highly qualified increases steadily as the proportion of highly qualified neighbours increases, conditional on county of origin. There is *no* indication here that being brought up in neighbourhoods at either end of the distribution of qualification levels makes things disproportionately better or worse – the relationship is predominantly linear.

Figure 2 shows the relationship once family background controls are included. We see more evidence of a non-linear relationship, and the average effect is attenuated. An individual from a neighbourhood in the top decile of the educational distribution is around 5-6 percentage points more likely to achieve A-levels than someone from the bottom decile – in line with the parametric estimates. However, it appears that most of the neighbourhood effect is attributable to individuals originating from neighbourhoods in the third quartile of the distribution - those with between 10 and 15% of adults with A-levels and higher qualifications. Improvements in neighbourhood status below the median and above the seventy fifth percentile have relatively weak effects on attainment of these qualifications. At

not my main concern here, I simply include age 7 test scores to remove variation attributable to abilities or early education. Removing the early test scores from the regression makes almost no difference to the estimated neighbourhood effect, though it almost doubles the parameter on predicted school quality. The implication is that even if school quality is endogenous, there is no discernible transmission of bias to the estimated neighbourhood parameter. The elasticity of individual educational attainments with respect to school quality is 0.345 for A-level attainments and –0.262 for no qualifications, and the coefficient is highly significant (*p*-value<0.0001). These elasticities are almost identical to the estimated impact of childhood neighbourhood. According to these IV estimates, childhood neighbourhood has an effect on adult attainments of council tenants which is at least as large as the effect associated with the type of school attended.

[14] Including parental education or interest in the social tenants' models has only a small impact on the neighbourhood coefficient. See the notes at the foot of Table 5.

its steepest, in wards with 10% of adults holding higher qualification, the slope is around four times the average. The 10% confidence intervals here are wide, so we should be cautious in placing too much emphasis on this.

Looking now at lower qualifications, Figure 2 graphs the association between the proportion of the cohort achieving only the lowest levels of qualifications by age 33 (no qualifications, CSE below grade 1), using similar methods. The relationship, with county controls only, mirrors that for A-levels and above, falling steadily as average neighbourhood qualification levels increase. After controlling for parental background, the probability of gaining no qualifications still falls steadily from neighbourhoods with the lowest educational status right up the top decile.

Figure 3 shows the relationship for social tenants only, to minimize parental selection effects without parental controls. The overall impression is similar to that in Figure 1 and Figure 2, though the estimated impact of neighbourhood on educational failure is much higher than we obtained in previous estimates – including those in Table 5. Children of council tenants resident at the 90th percentile of neighbourhoods were around 10 percentage points less likely to gain no qualifications than those at the 10th percentile[15].

The key story from these semi-parametric results is that marginal improvements in residential neighbourhood reduce the probability of failure in the educational system throughout the distribution of neighbourhood educational status. The effects of neighbourhood on higher attainments appear to be concentrated above the middle of the distribution, and below the top quartile – this could be interpreted as evidence for threshold effects around some critical mass in the centre of the distribution, but the evidence is weak. Nothing here indicates that the extremes of neighbourhood deprivation or privilege matter disproportionately.

5.6 Effects on abilities and attitudes

The results of Sections 5.1 to 5.5 focus on the effects of childhood neighbourhood educational status on individual educational attainments by age 33. We found that living in a higher educational status neighbourhood at age 16 leads to higher educational attainments by

[15] Though, the elasticity at the 10% point on the horizontal axis is about –0.2, the same as the full sample.

age 33. There are numerous channels of influence of neighbourhood on educational choices from teenage years to adulthood. These could include direct influences on abilities and aptitudes, motivation to achieve qualifications, incentives on whether to stay on at school, drop out or whether to continue to higher education. We can shed some light on this by looking at measured academic abilities, rather than on an individual's educational trajectory, using the standard tests given to the NCDS cohort members at age 16.

Table 6 presents some results for this exercise, for men and women[16]. All the estimates are conditional on our school quality measure - the proportion of own-sex studying for GCE O-levels - and scores in comparable tests at age-11. The first four columns show the parameter estimates for all tenancy groups, in reading and maths test, with and without parental background controls. The neighbourhood elasticities are quite low, which is unsurprising since we are estimating the effect of teenage neighbourhood on gains in test scores between age-11 and age-16. Introducing parental controls halves the estimated coefficients, with resulting elasticities of around 0.007 for reading and 0.020 for mathematics. Children from the 90th percentile in the distribution of neighbourhoods achieved reading test scores that were on average 1.3% higher than those of children from the 10th percentile. For mathematics, the gain was around 3.6%.

Columns 5 to 8 show similar estimates for council tenants only. Note that introducing parental controls has a relatively small effect on the estimated coefficients on neighbourhood status. This supports the assumptions of the method of Section 3.4, that parental characteristics are only weakly correlated with neighbourhood for council tenants. Even with parental controls, the results indicate that children from social housing at the 90th percentile of neighbourhoods achieved reading scores that were 2.8% better, and maths scores which were 5.8% better than their counterparts living in neighbourhoods at the 10th percentile. Since we control for age-11 test scores and secondary school performance, these figures will not include any neighbourhood effects on primary school age achievements, or on basic secondary school quality.

Questions on attitudes to education in the NCDS at age 16 allow us to explore the influence of neighbourhoods on educational expectations. The 1974 survey asks the child at

[16] Gender-neighbourhood interactions were insignificant.

what age range he or she expects to leave school, and whether he or she expects to study for A-levels or equivalent. Using an ordered probit model with the same controls as in Table 6 suggests no effect from neighbourhood educational status on aspirations for girls, conditional on secondary school quality and age-11 mean test scores. School quality is, however, strongly associated with educational aspirations for girls. More interestingly, neighbourhood status has a positive influence on educational aspirations of boys, over and above secondary school quality. A one percentage point increase in the ward-proportion of highly qualified adults translates into a 0.18% (t = 2.150) increase on the proportion who say they are very likely to study for A-levels (the proportion in this group is 36%). This is a small effect, but similar in magnitude to the marginal effect associated with better schools (0.184, t = 8.21). This means that boys from neighbourhoods at the 90th percentile were three-and-a-quarter percentage points more likely to expect to study for A-levels than those at the 10th percentile – a relative shift of just under 10%. This gender difference could measure a real difference in behavioural response, but may just reflect the weakness of our neighbourhood educational status variable as a proxy for female role models.

6. An Overview of the Spatial Contribution to Educational Attainment

6.1 Intergenerational mobility and neighbour correlations in the NCDS

All the approaches adopted above suggest that neighbourhood human capital levels have some impact on educational attainments, albeit relatively small once we allow for parental effects. We have focussed on relatively small local communities defined by Census wards, and have looked for ways of getting robust and plausible estimates of the impact of these communities. This section presents summary results which characterise the relative importance of geographical areas and parents on educational outcomes. The focus is on parental and area-level educational status only, in terms of *educational mobility* as measured by the traditional immobility parameter – see Atkinson (1981), Dearden, Reed *et al.* (1997), and Solon (1989; 1999) – and on *inter-neighbour correlations* in educational outcomes.

Kremer (1997) argues that the existence of neighbourhood effects has little impact on equilibrium inequality or intergenerational mobility, largely because most of the distribution in earnings is not explained by family background factors and because neighbourhoods and families are not permanently linked. Nevertheless, if we are focussing on what *can* be explained, it is reasonable to ask: a) what proportion of the variance in educational attainments could be attributable to neighbourhood and b) what proportion of the persistence in economic status across generations of the same family is attributable to neighbourhood or area of upbringing? Table 7 answers the first question, based on the correlation between outcome educational attainments and the attainments of other cohort members originating from the same Census ward (at age 16). Table 8 answers the second question for various definitions of neighbourhood – Census enumeration district, ward, and county.

6.1.1 Inter-neighbour correlations

We can obtain an upper bound to the influence of neighbourhood by the correlation between an individual's adult attainments and those of his or her neighbours as a child. This approach has been applied in the sibling-correlations literature to give an upper bound to the impact of family background Solon, Corcoran *et al.* (1991) and has also been used in the neighbourhood context by Solon, Page *et al.* (2000) to bound neighbourhood effects on education in the US. Table 7 presents the regression coefficients l from the model

$$\hat{h}_{ij} = l\hat{\bar{h}}_{j-i} + \mathbf{x}'_{ij} b + w_i$$

where $\hat{h}_{ij}$ is years in education for individual *i*, resident in ward *j* at age 16, standardised to unit variance. Variable $\hat{\bar{h}}_{j-i}$ is the mean years of education for other children brought up in ward *j*

$$\bar{h}_{j-i} = \frac{1}{J-1}\sum_{k\neq i}^{J} h_k \ ,$$

standardised to unit variance. Since $Var(\hat{h}_i) = Var(\hat{h}_j)$ the coefficient l is a consistent estimate of the correlation between an individual's education and that for the average other child in the childhood ward of residence. This is clearly an upper bound on direct neighbourhood effects, since it includes correlation in outcomes attributable to correlations between neighbours family background characteristics.

The OLS estimates in the first row 1 of the first column in Table 7 suggest an inter-neighbour correlation of, at most, 0.11. Following Solon, Sage and Duncan (2000), the estimates in row 2 weight the regressions by the number of other cohort members in each ward, because wards with more observed residents provide more information. This pushes up the estimate to 0.16. Moving across the columns of Table 7, the estimated neighbour correlation falls as we introduce county dummies to remove correlation induced by institutional differences in education and local labour market factors at the county level, and then again once parental education is included. Adjusting for parental similarities, the correlation between outcome education years for a child and his or her average neighbourhood peer is between 0.043 and 0.065. This may understate the overall effect if there are neighbourhood factors which operate via parental education. An interpretation of these correlation coefficients is that a child could expect to increase his or her time in education by between 3.2 to 11.8 weeks if brought up amongst children destined to stay in education for 1.4 years longer than average. These results suggest slightly weaker neighbourhood effects on education than in the US. Solon, Page *et al.* (2000) using US PSID data from the 1970s, get unadjusted correlations of 0.153-0.192, falling to 0.062-0.104 when adjusted for parental income.

6.1.2 Intergenerational mobility

The estimates in Table 8 are the parameters in the model:

$$\tilde{h}_i^c = r_1 \tilde{h}_i^n + r_2 \tilde{h}_i^p + e_i \qquad (24)$$

where the tilde indicates standardised, unit variance, zero mean transformations. The first rows constrains r_1 to zero, the second row constrains r_2 to zero, rows three and four present the unconstrained parameters. The dependent variable is either standardised years of education, or a dummy indicating attainment of A-level qualifications or higher at age 33. Standardisation of the variables ensures that the coefficients are unaffected by general changes in the variance of human capital across generations, and give the response in standard deviations to a one standard deviation change in the regressor[17]. In the probit case, the marginal effect just gives the effect of a one standard deviation change in the explanatory variable on the probability of gaining A-levels, since we cannot observe or adjust for changes in the variance of the underlying latent child's human capital.

The basic educational years mobility parameter in row 1 is in line with other estimates in the literature. Looking at row 2, column 1, the parameter estimate of 0.263 means that children who end up 0.263 standard deviations above the mean in the distribution of time in education come from neighbourhoods which were one standard deviation above the mean. Moving right across Table 8 to column 3, then to column 5, the influence of area diminishes as the area definition broadens from ED to ward to county. The ward-level estimates in column 7, which include county dummies are barely different from those in column 3, suggesting a minimal role for county level effects in intergenerational educational mobility, conditional on neighbourhood. The estimated parameters in the probit models (the even columns) show the same pattern,

Unsurprisingly, once we include both neighbourhood and parental education in the equations (rows 3 and 4), the estimated independent effects of parental education and neighbourhood reduce – by the percentages shown in rows 5 and 6. We can interpret the percentages in row 5 as the proportion of the intergenerational mobility parameter attributable to neighbourhood status. The percentage in row 6 is the proportion of the association between neighbourhood and educational attainment that is explained by parental education. At ED level, neighbourhood status explains around 13% of intergenerational immobility. At ward level, neighbourhood explains 8-10%. County differences explain very little of the intergenerational immobility parameter conditional on parental education (less than the standard error), suggesting only a small role for broader institutional effects, or labour market induced effects such as the formation of expectations of the market returns to education.

More generally, we could specify (20) as:

$$\tilde{h}_i^c = g\left(\tilde{h}_i^n, \tilde{h}_i^p\right) + e_i \qquad (25)$$

[17] An asymptotically equivalent approach for the single regressor case is to rescale the parameter estimates by multiplying by s^p / s^c (see Solon, 1999).

This unrestricted relationship between child's, parent's and mean neighbourhood educational attainments can be estimated by bivariate kernel regression.[18] The results are shown in Figure 4. This provides a clear illustration of the relative effects of parental background and neighbourhood on educational attainment. Looking at the regression surface, there is little evidence of complementarities between parental and neighbourhood education: children from parents at the 90th percentile in the educational distribution can expect to end up roughly two and a half deciles above their counterparts at the 10th percentile, regardless of neighbourhood status[19]. Parental effects are highly non-linear – over half of this impact occurs within the top quintile of the parental distribution. Compared to parental education, neighbourhood has a relatively small impact, shifting children of similar parentage up the educational distribution by around one decile on average. Reading along the median outcome contour, we can see that a child at the top of the distribution of neighbourhood educational status can expect to reach median educational attainments, even if their parents' educational score lies at the 35th percentile. By contrast, someone in a neighbourhood at the very bottom of the distribution must have parents educated to about the 85th percentile.

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[18] The estimator is the Nadaraya-Watson estimator with a bivariate Gaussian kernel, estimating the conditional mean $E\left[\tilde{h}_i^c \mid \tilde{h}_i^n, \tilde{h}_i^p\right]$ on a 40 × 40 matrix of regressor grid points. Since we do not have outcome, parental and neighbourhood measures on the same metric, the regression uses scores constructed from the raw variables based on their rank in the empirical distribution. The neighbourhood educational score is the rank of the neighbourhood in the distribution of ward-proportions with high qualifications. We generate the parental educational score by ranking mother's and father's years in education. Where there are ties, rank is within educational categories according to social class in 1974. Mother's and father's educational scores combine to make the family ranking. The outcome educational score is based on ten ordered qualifications categories, with ranking within categories by time in education. The scores are all normalised so that they give the ranking on a scale of zero to one.

[19] This was what we found in Section 5.2.4.

6.2 Has much changed since the 1970s?

6.2.1 Changes in the area educational effects

It would certainly be interesting to compare these results for children raised in the 1960s and 1970s with a later cohort. Unfortunately, the more recent cohort in the 1970 British Cohort Study (BCS), has no codes for neighbourhood area of residence. The smallest geographical area which we can assign to a child's residential address is District Health Authority (DHA) at age 10, which can be matched to 1981 Census data. We can find some point of comparison here with the earlier cohort by comparing area education effects at DHA level in the BCS with area effects at Local Education Authority level in the NCDS. These are similar in terms of aggregation level.

Table 9 shows coefficients in the intergenerational mobility equation for the NCDS and BCS. Outcomes are at age 33 for the NCDS, but age 26 for the BCS. Since education is complete by age 26 for most individuals, the difference in ages is not problem. Looking at the results for years of education in row 1, it seems that educational mobility in terms of time in education changed little between the 1970s and 1980s. The immobility parameter is virtually unchanged between columns 1 and 5 and any difference is insignificant. In terms of higher qualifications, mobility appears to *decrease* by this measure: although the probit marginal effect estimates are higher in columns 2 and 6, the relative effect at the mean (dividing by the proportion with high qualifications) increases from 0.44 to 0.51[20]. Controlling for regional effects in columns 3, 4 and 7, 8 makes only a slight difference to the results. Comparing the 1980s and 1970s area effects, whether conditional (row 2) or

[20] This result is not robust to alternative ways of cutting the data. If we look at the proportions of the top 17% in the parental education distibution for the BCS and NCDS (this figure corresponds to the proportion of families with fathers who have a degree in the BCS and for whom we observe education at age 26) we find that the probability of gaining a degree or higher conditional on this parental educational background increased from 31.6% to 49.4%. At the same time the probability of a child from the bottom 83% gaining a degree increased from 8.2% to 15%. The relative improvement in the chances for those from a better educated background getting a degree is 56% versus 83% for those from less educated parents. The index of immobility (the sum of diagonal cell proportions, minus the sum of off diagonals) decreases from 0.63 to 0.58.

unconditional (row 3) on parental education, shows virtually no change in the association between area and educational outcome between the decades.

Summarising, using the limited area data available for comparison, there is no evidence of weakening of area effects on educational attainments, but some mixed evidence of a strengthening of the link with parental education. This last result is surprising, but is consistent with findings in Blanden, Goodman *et al*. (2001) that income mobility in Britain *decreased* between the 1970s and 1980s.

6.2.2 Segregation and spatial educational inequalities

Appendix D discusses changes in the spatial distribution of education using Census data from 1971, 1981 and 1991. The evidence from the Census data is that there has been virtually no change in the variance of the distribution of education across wards, though this does not deny that neighbourhoods may have changed rank in the distribution. The consensus from the US is that there has been increased segregation, and increase in the correlation between the characteristics of individuals and their neighbours (see Kremer, 1997; or Gephart, 1997 for references). In conjunction with structural neighbourhood effects, this would imply increasing inequality and intergenerational immobility, though Kremer argues that these effects are small. Increasing segregation implies a decrease in the variance of education within neighbourhoods and a widening of the distribution of mean education across neighbourhoods, holding the overall variance constant. This follows from the decomposition of variance:

$$Var\left(E\left[h_i \mid n\right]\right) = Var(h_i) - E\left[Var\left(h_i \mid n\right)\right] \qquad (26)$$

For a given overall variance in education across individuals, an increase in the correlation between individuals' education within neighbourhoods n implies a decrease in the variance within neighbourhoods $E\left[Var\left(h_i \mid n\right)\right]$, hence an increase in the variance of the mean across neighbourhoods $Var\left(E\left[h_i \mid n\right]\right)$. Appendix D shows, however, that there has been virtually no such increase from 1971 to 1991 in Britain, once we correct for exogenous changes in $Var(h_i)$ attributable to an increase in average educational achievements. From this evidence, neighbourhood effects are likely to have contributed little to any *increases* in inequality and social immobility. This does not detract from their potential importance in the static cross-sectional distribution.

7. Summary and Concluding Remarks

Children's academic attainments are sensitive to community influences. The methods in this study focus on identifying a relationship between the proportion of highly qualified adults in a child's neighbourhood and his or her educational attainments. The results show that the association between community attainments and child attainments is robust, under different empirical strategies that compensate for parental selection on schools and neighbourhood. In particular, children of social tenants brought up in Britain in the 1970s were influenced by the proportion of highly qualified adults in their neighbourhood, and with those components of neighbourhood educational status which are correlated with the physical characteristics of owner-occupied housing. These effects are at least as large as the effects estimated on the population as a whole. The fact that social tenants benefit is in contrast with the policy conclusions in Duncan (1994), who suggests that the weakness of effects on disadvantaged groups means that policy to redistribute resources between wealthy and poor neighbourhoods may have adverse effects.

Variation in educational status predicted from owner-occupied housing structure appears to have a stronger influence on the adult attainments of social tenants than does variation attributable to the proportion of social tenants. This could indicate that children resident in social housing are especially sensitive to the quality of the local residential community, outside their estate. The sensitivity of social tenants to home-owner characteristics – and the persistence of neighbourhood effects over and above measures of secondary school quality – supports the collective socialisation or adult role model effects in the sociological literature (Jencks and Mayer, 1990), the importance of social capital (Coleman, 1988) if this is related to the neighbourhood stock of human capital, or the influence of expectations formation within the local community – Roemer and Wets (1994), Streufert (1991). Broadly speaking, the results provide evidence of educational spillover effects from the community to the individual. The influence of community can be traced back to scores on attainment tests administered at age 16 (and earlier, at age 7 – see Gibbons, 2001).

Reviewing the estimates in this study, we conclude that the probability of a child attaining high qualifications responds to the community proportion with these qualifications with an elasticity of around 0.1 in the average neighbourhood. The effect could be up to four-times greater than this in the centre of the distribution of neighbourhoods and weaker in the tails. Children of social tenants in the 1970s were similarly sensitive, though IV estimates that correct for measurement error, parental and school-based selection are substantially higher, with elasticities of around 0.26.

The table below summarises the key findings:

	Elasticity at mean neighbourhood		10^{th} to 90^{th} percentile change in neighbourhood	
	A-Levels +	Low quals.	A-Levels +	Low quals.
All tenancy groups, conditional on neighbourhood, area and school quality	0.14	-0.21	7.5	-5.6
All tenancy groups, conditional on background, area and school (IV)	0.10	-0.14	5.2	-3.9
Social tenants, conditional on school, area and early attainments	0.10	-0.07	2.6	-3.5
Social tenants, IV from owner occupied property	0.26	-0.20	7.1	-9.8

Nothing in the results indicates that community effects are mediated via family circumstances, although there are significant interactions with indicators of parental interest in a child's education. We can read this as meaning that parental interest affects the returns to neighbourhood and school performance in the human capital production function, or that the returns affect parental interest – these are observationally equivalent in the data available here.

Although the evidence is based on children who were teenagers some thirty years ago, there is no reason to believe that the underlying structural relationships will have changed in the intervening period. Comparison of broader area effects on children raised in the 1970s and 1980s using two different cohort studies provides no evidence of a weakening of the area components of intergenerational educational mobility.

The overall finding of this paper is that neighbourhoods do influence outcomes, regardless of family resources. In particular, children's educational attainments are sensitive to the adult educational composition of their neighbourhood. But we find nothing to contradict the general consensus that neighbourhoods determine only a small proportion of the variation in individual outcomes, and that family background matters more. Correlation between total time in education and the education of others from the same child-hood ward is relatively weak: an upper bound on the inter-neighbour correlation in educational outcomes is 0.16. A more conservative estimate places this at around 0.07. These inter-neighbour spillover effects in educational attainment *do* imply higher benefits from tackling educational disadvantage at the neighbourhood level, rather than on an individual or family basis. But, the evidence from this paper is that these additional benefits are quite small.

Table 1: Area-only models of men's, age 33 qualifications

	I			II			
	Low	High	| t |	Low	High	| t |	Mean
Ward proportion highly qualified	-0.497	0.673	6.102	-0.314	0.420	3.749	0.117
School quality	-	-	-	-0.324	0.433	19.825	0.278
Unskilled workers	0.259	-0.349	1.734	0.118	-0.157	0.762	0.074
Unemployment rate	0.599	-0.809	2.164	0.515	-0.688	1.600	0.039
Economically active men	-0.023	0.032	0.253	0.122	-0.163	1.292	0.606
Economically active women	-0.038	0.051	0.749	-0.062	0.083	1.218	0.572
One year migrants	-0.010	0.013	0.083	0.060	-0.080	0.611	0.092
New com. immigrant	-0.045	0.061	0.619	0.067	-0.089	0.797	0.027
Average dwelling size	-0.052	0.070	3.444	-0.024	0.033	1.529	4.876
Households lacking amenities	0.435	-0.588	1.808	0.408	-0.545	1.591	0.028
Social housing	0.073	-0.099	2.516	0.088	-0.118	2.878	0.384
City ward	-0.034	0.046	2.552	-0.027	0.036	1.900	0.410
High population	0.001	-0.002	0.112	-0.001	0.001	0.077	0.249
Agricultural employment	0.237	-0.320	2.302	0.135	-0.181	1.262	0.027
Mining, manufacturing employment	-0.060	0.081	1.053	-0.114	0.153	1.868	0.372
County effects	χ^2_{60} = 75.17, P=0.090			χ^2_{60} = 104.25, P=0.00			
Predicted group probability	0.187	0.338		0.179	0.343		
Log likelihood		-4504.80			-3375.03		
Pseudo R^2		0.044			0.097		
Sample size		4538			3637		

Three category ordered probit estimates.

Including ward professional and managerial employees reduces parameter on ward education to –0.223/+0.299 (t=2.214) in column II, but is not itself highly significant (t=1.54).

Neighbourhood educational measure is proportion of adults in high qualification category in cohort member's age-13 residential ward. School quality is proportion of boys age 15 studying for GCEs at cohort members' school.

Table 2: Neighbourhood education and family effects on men's age-33 qualifications

	I			II			III			
Qualification group:	Low	High	| t |	Low	High	| t |	Low	High	| t |	Mean
Ward education	-0.200	0.278	3.45	-0.166	0.223	2.85	-0.174	0.230	2.96	0.117
School performance	-	-	-	-0.138	0.185	8.90	-0.076	0.100	3.59	0.278
School type:	-	-	-	-	-	-	χ^2_5 = 25.59, P=0.0001			
Grammar	-	-	-	-	-	-	-0.080	0.106	4.52	0.116
Secondary modern	-	-	-	-	-	-	0.007	-0.010	-0.66	0.211
Independent	-	-	-	-	-	-	-0.060	0.080	2.11	0.040
Grant maintained	-	-	-	-	-	-	-0.088	0.116	2.39	0.029
Other non-LEA	-	-	-	-	-	-	0.029	-0.039	1.07	0.024
Mother education yrs	-0.015	0.021	4.25	-0.013	0.018	3.64	-0.012	0.017	3.41	15.064
Father education yrs	-0.017	0.024	5.94	-0.015	0.021	5.22	-0.015	0.020	4.99	15.211
Father's age	-0.001	0.002	1.92	-0.001	0.001	1.69	-0.001	0.001	1.66	30.540
Dwelling size	-0.009	0.012	2.27	-0.005	0.007	1.37	-0.004	0.006	1.13	4.978
Tenure:	χ^2_4 = 33.43, P=0.000			χ^2_4 = 34.69, P=0.000			χ^2_4 = 34.17, P=0.0000			
Tenure missing	0.082	-0.113	2.60	0.082	-0.110	2.65	0.087	-0.115	2.80	0.020
Council tenant	0.058	-0.080	5.22	0.060	-0.080	5.37	0.058	-0.077	5.23	0.366
Private rental	0.023	-0.032	1.35	0.022	-0.029	1.23	0.018	-0.023	0.99	0.050
Other tenure	0.052	-0.072	2.31	0.049	-0.066	2.17	0.050	-0.066	2.19	0.036
Parental interest	χ^2_{11} = 162.14, P=0.000			χ^2_{11} = 141.73, P=0.000			χ^2_{11} = 136.87, P=0.000			
Family size (ln kids)	0.046	-0.063	5.15	0.039	-0.053	-4.40	0.039	-0.052	4.39	1.042
Age-7 test scores	-0.627	0.868	20.49	-0.578	0.776	18.54	-0.558	0.740	17.65	0.530
Age-7 tests missing	-0.415	0.575	16.48	-0.382	0.512	14.96	-0.371	0.492	14.49	0.112
Social housing	-0.010	0.014	0.96	-0.013	0.017	1.19	-0.013	0.017	1.21	0.384
City ward	-0.014	0.090	1.14	-0.015	0.020	1.25	-0.014	0.019	1.19	0.410
High population	-0.009	0.013	0.78	-0.008	0.011	0.67	-0.009	0.012	0.74	0.249
LA agriculture	0.102	-0.142	1.24	0.110	-0.148	1.33	0.111	-0.147	1.33	0.027
LA unemployment	0.702	-0.973	1.96	0.642	-0.861	1.79	0.630	-0.835	1.75	0.040
County effects	χ^2_{60} = 86.06, P=0.011			χ^2_{60} = 85.52, P=0.017			χ^2_{60} = 77.98, P=0.059			
Mean	0.178	0.343		0.178	0.343		0.178	0.342		
Log likelihood		-2962.24			-2920.75			-2908.15		
Pseudo R^2		0.207			0.218			0.222		
Sample size		3637			3637			3637		

Three category ordered probit estimates.

Neighbourhood educational measure is proportion of adults in high qualification category in cohort member's age-13 residential ward. School performance is proportion of boys age 15 studying for GCEs.

Estimation of model of first column using full available sample of 4538 men gives marginal effect from neighbourhood education of – .231 on the low category and .310 on the high category (t = 4.306, p-value = 0.0000). The coefficient is not significantly different from estimate on the smaller subsample for which school performance is observable.

Replacing county dummies with 1974 LEA dummies gives marginal effect –0.18/+0.24 (t=3.149, P=0.002) in column 3.

Table 3: Sensitivity of neighbourhood effect to parental characteristics and early abilities

	With additional controls			Without controls		
Additional control variables:	Low	High	| t |	Low	High	| t |
Family income dummies[1] χ^2_{21}=1502 P=0.000, N = 2525	-0.152	0.212	2.134	-0.169	0.237	2.376
Father and mother's social class[1] χ^2_{13}=35.65 P=0.001, N = 3345	-0.136	0.190	2.202	-0.184	0.256	2.975
Father & mother's socioeconomic group[1] χ^2_{31}=1338.1 P=0.000, N=3392	-0.127	0.180	2.074	-0.171	0.230	2.801
Parental interest dummies[2] χ^2_{11}=141.8 P=0.000, N=3637	-0.166	0.223	2.853	-0.208	0.278	3.512
Early attainments (mean of age 7 tests)[2]	-0.166	0.223	2.853	-0.189	0.246	3.014
Reading ability at age 11	-0.152	0.202	2.669	-0.166	0.223	2.853

t=15.406

Three category ordered probit estimates.

1. Other regressors as in Table 2, column 1
2. Other regressors as in Table 2, column 2

Table 4: Neighbourhood education and family effects on men – 2-step estimates

	I			II			III			
Qualification group:	Low	High	| t |	Low	High	| t |	Low	High	| t |	Mean
Ward education	-0.242	0.336	2.48	-.198	0.266	2.01	-0.219	0.289	2.17	0.117
School performance	-	-	-	-.137	0.184	9.05	-0.074	0.098	3.53	0.278
School type:	-	-	-	-	-	-	χ^2_5 = 24.54, P=0.0002			
Grammar	-	-	-	-	-	-	-0.080	0.106	4.25	0.116
Secondary modern	-	-	-	-	-	-	0.008	-0.010	0.67	0.211
Independent	-	-	-	-	-	-	-0.061	0.081	2.14	0.040
Grant maintained	-	-	-	-	-	-	-0.087	0.115	2.61	0.029
Other non-LEA	-	-	-	-	-	-	0.029	-0.039	1.10	0.024
Mother education yrs	-0.015	0.021	4.61	-.013	0.018	3.95	-0.012	0.016	3.66	15.064
Father education yrs	-0.017	0.025	6.39	-.015	0.021	5.55	-0.015	0.020	5.42	15.211
Father's age	-0.001	0.002	1.91	-.001	0.005	1.69	-0.001	0.001	1.65	30.540
Dwelling size	-0.008	0.017	2.17	-.005	0.007	1.29	-0.004	0.006	1.05	4.978
Tenure:	χ^2_4 = 32.36, P=.0000			χ^2_4 = 33.46, P=0.0000			χ^2_4 = 32.52, P=0.0000			
Tenure missing	0.082	-0.114	3.07	.083	-0.111	3.01	0.088	-0.117	3.15	0.020
Council tenant	0.058	-0.080	5.05	.060	-0.080	5.21	0.058	-0.077	5.04	0.366
Private rental	0.023	-0.032	1.13	.022	-0.029	1.05	0.018	-0.023	0.86	0.050
Other tenure	0.051	-0.070	2.28	.049	-0.066	2.22	0.049	-0.065	2.21	0.036
Parental interest	χ^2_{11} = 169.43, P=0.0000			χ^2_{11} = 145.48, P=0.0000			χ^2_{11} = 139.36, P=0.0000			
Family size (ln kids)	0.045	-0.063	5.03	.039	-0.052	4.25	0.039	-0.052	4.25	1.042
Age-7 test scores	-0.626	0.868	22.03	-.577	0.777	19.88	-0.558	0.740	18.77	0.530
Age-7 tests missing	-0.415	0.576	18.19	-.382	0.513	16.38	-0.372	0.493	15.69	0.112
LA estate	-0.012	0.016	1.04	-.014	0.019	1.22	-0.014	0.020	1.26	0.384
City ward	-0.014	0.019	1.21	-.015	0.021	1.32	-0.015	0.019	1.26	0.410
High population	-0.008	0.012	0.74	-.007	0.008	0.66	-0.008	0.011	0.71	0.249
LA agriculture	0.100	-0.138	1.11	.109	-0.145	1.19	0.108	-0.144	1.18	0.027
LA unemployment	0.667	-0.926	2.00	.617	-0.829	1.83	0.596	-0.789	1.75	0.040
County effects	χ^2_{60} = 78.07, P=0.0585			χ^2_{60} = 84.48, P=0.0204			χ^2_{60} = 74.11, P=0.1040			
Exogeneity test	χ^2_1 = 1.333, P=0.248			χ^2_1 = 0.323, P=0.570			χ^2_1 = 0.336, P=0.562			
1st step instruments	χ^2_2 = 668.08, P=0.0000			χ^2_2 = 1190.61, P=0.0000			χ^2_2 = 661.98, P=0.0000			
Mean	0.178	0.343		0.178	0.343		0.178	0.342		
Log likelihood		-2964.61			-2922.50			-2909.76		
Pseudo R^2		0.207			0.218			0.221		
Sample size		3637			3637			3637		

Three category ordered probit estimates.

Neighbourhood educational measure is predicted proportion of adults in high qualification category in cohort member's age-13 residential ward. Ward proportions with more than seven rooms, council tenants used as instruments.

Other variables as Table 2.

Table 5: Neighbourhood education effects on social tenants, age 33 qualifications

	I			II			III			IV			
Qualification group:	Low	High	| t |	Low	High	| t |	Low	High	| t |	Low	High	| t |	Mean
Ward education	-0.345	0.251	2.70	-0.244	0.178	2.11	-0.726	0.528	2.47	-0.673	0.489	2.50	.095
School quality	-	-	-	-0.191	0.140	6.25	-	-	-	-0.365	0.265	6.73	.233
Early attainments	-	-	-	-0.934	0.686	19.11	-	-	-	-0.876	0.636	19.01	.510
Missing	-	-	-	-0.500	0.366	13.29	-	-	-	-0.455	0.330	12.86	.090
Male	-0.078	0.056	5.20	-0.076	0.056	5.56	-0.077	0.056	5.17	-0.071	0.052	5.20	.471
Local social housing	-0.001	0.005	0.37	-0.000	0.000	0.01	-0.018	0.013	0.99	-0.011	0.008	0.63	.774
City ward	-0.012	0.009	0.57	-0.025	0.019	1.30	-0.015	0.011	0.75	-0.028	0.021	1.60	.446
High population	-0.018	0.013	0.38	-0.016	0.012	0.84	-0.014	0.010	0.68	-0.009	0.007	0.50	.284
LA agriculture	0.020	-0.015	0.13	0.009	-0.007	0.06	0.010	-0.007	0.05	-0.000	0.000	0.00	.022
LA unemployment	1.334	-0.970	2.31	1.051	-0.770	1.95	1.018	-0.741	1.97	0.491	-0.357	1.01	.045
County effects	χ^2_{60}=110.99, P=0.0000			χ^2_{60}=94.44, P=0.0030			χ^2_{60}=102.71, P=0.0005			χ^2_{60}=97.61, P=0.0015			
Exogeneity test	-			-			χ^2_{4}=6.32, P=0.1762			χ^2_{9} = 7.963, P=0.5379			
Predicted group prob.	0.324	0.179		0.324	0.179		0.324	0.178		0.325	0.179		
Log likelihood	-2789.71			-2542.99			-2790.06			-.2537.15			
Pseudo R^2	0.029			0.115			0.029			0.117			
Sample size	2818			2818			2818			2818			

Three category ordered probit estimates.

Predicted neighbourhood education uses proportion of owner occupier properties with one-two rooms, seven or more rooms, lacking various amenities.

School quality is proportion of own sex, age 15 studying for GCEs, predicted by school type and pupil-teacher ratio to remove catchment area effects on school quality (but not peer group effects or correlation between pupil performance due to selection by schools or by parents). Exclusion of early attainments measure tests sensitivity to selection on ability to high performing schools, by schools or parents – without early attainment control estimates in column IV are -.706/448 for school quality parameter, -.628/509 for neighbourhood parameter. Neighbourhood parameter is only slightly sensitive, whilst the school performance parameter almost doubles.

Inclusion of parental education gives marginal neighbourhood effect of –0.29/+0.21 (t = 2.263) in column I, -0.730/+0.529 (t = 2.496) in column III.

Inclusion of parental interest dummies gives marginal neighbourhood effect of –0.24/+0.17 (t = 1.984) in column I, -0.608/+0.438 (t = 2.164).in column III.

Neighbourhood instruments have p-value < 0.0001% in prediction equations. Inclusion of ward-proportion in council housing in instrument set gives estimates of neighbourhood marginal effect almost identical to non-instrumented estimate: e.g.+0.185/-0.254 with school quality control.

Table 6: Teenage attainments of NCDS cohort, age 16 tests, conditional on age 11 tests and schooling

	All tenancy groups				Social tenants only			
	Reading		Arithmetic		Reading		Arithmetic	
1971 ward education	0.160 (0.032)	0.072 (0.034)	0.482 (0.067)	0.200 (0.069)	0.167 (0.076)	0.154 (0.076)	0.365 (0.158)	0.315 (0.158)
Secondary school performance	0.054 (0.007)	0.040 (0.008)	0.374 (0.016)	0.319 (0.016)	0.076 (0.018)	0.069 (0.018)	0.439 (0.039)	0.424 (0.039)
Age 11 test log-score	0.567 (0.012)	0.542 (0.012)	0.475 (0.010)	0.447 (0.010)	0.589 (0.018)	0.571 (0.019)	0.411 (0.015)	0.398 (0.015)
Male	0.011 (0.005)	0.010 (0.005)	0.107 (0.010)	0.109 (0.010)	0.017 (0.009)	0.017 (0.009)	0.107 (0.019)	0.108 (0.019)
1971 County effects	χ^2_{60}=164 P=0.000	χ^2_{60}=112 P=0.000	χ^2_{60}=131 P=0.000	χ^2_{60}=193 P=0.000	χ^2_{60}=97.6 P=0.002	χ^2_{60}=99 P=0.001	χ^2_{60}=179 P=0.004	χ^2_{60}=164 P=0.000
Log family size	-	-0.052 (0.006)	-	-0.052 (0.012)	-	-0.060 (0.010)	-	-0.061 (0.020)
Rooms in family home	-	0.000 (0.002)	-	-0.002 (0.004)	-	-0.009 (0.007)	-	-0.010 (0.013)
Father's age	-	-0.001 (0.001)	-	0.0015 (0.0008)	-	-0.001 (0.001)	-	0.0036 (0.0014)
Father's education	-	χ^2_2=5.5 P=0.065	-	χ^2_2=38.6 P=0.000	-	χ^2_2=2.7 P=0.265	-	χ^2_2=20.0 P=0.000
Mother's education	-	χ^2_2=14.3 P=0.001	-	χ^2_2=32.0 P=0.000	-	χ^2_2=11.3 P=0.003	-	χ^2_2=4.8 P=0.090
Tenancy group	-	χ^2_4=26.2 P=0.000	-	χ^2_4=46.0 P=0.000	-	-	-	-
Sample size	8304		8205		3250		3189	

Dependent variable is natural log of test scores.

Models are interval regression, to allow for upper and lower censoring.

Instrumenting school performance with school type and pupil-teacher ratio leaves results virtually unchanged.

Table 7: Inter-neighbour correlations in age-33 education

	Controls for gender only	Controls for County in 1971 and gender	Controls for County in 1971, gender and parents' education
Unweighted	0.107 (0.016)	0.087 (0.016)	0.043 (0.014)
Weighted by number in ward	0.159 (0.019)	0.128 (0.020)	0.065 (0.018)
Sample size	8237	8237	8237

Standard errors adjusted for clustering on 1971 Census ward.

Table 8: Area effects on intergenerational educational mobility

	ED		Ward		County		Ward | County	
	Years	A Levels+	Years	A Levels+	Years	A Levels+	Years	A Levels+
Standardised parental education only	0.382 (0.011)	0.143 (0.006)	0.382 (0.011)	0.143 (0.006)	0.382 (0.011)	0.143 (0.006)	0.379 (0.011)	0.142 (0.006)
Standardised area measure only	0.263 (0.011)	0.098 (0.005)	0.222 (0.010)	0.087 (0.005)	0.084 (0.010)	0.032 (0.005)	0.221 (0.011)	0.087 (0.005)
Standardised parental education | area	0.333 (0.011)	0.124 (0.006)	0.349 (0.011)	0.129 (0.006)	0.377 (0.011)	0.141 (0.006)	0.348 (0.011)	0.130 (0.006)
Standardised area | parents	0.159 (0.011)	0.064 (0.005)	0.130 (0.010)	0.056 (0.005)	0.047 (0.009)	0.018 (0.005)	0.130 (0.011)	0.056 (0.005)
	11212	9279	11212	9279	11212	9279	11212	9279
Percentage of familial intergenerational mobility attributable to area	12.8%	13.2%	8.6%	9.8%	1.3%	1.4%	8.2%	8.5%
Percentage of area effect attributable to parents	39.5%	34.7%	35.6%	35.6%	44.0%	43.8%	41.2%	35.6%

Proportion with A-levels plus in 1991 is 32.9%.

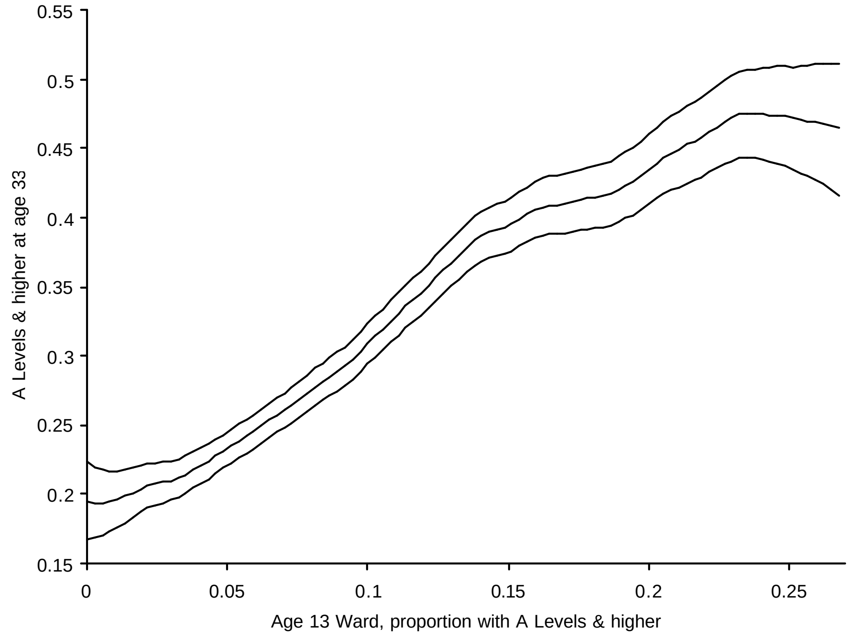
Table 9: Area effects on intergenerational educational mobility: comparison between 1970s and 1980s

	NCDS, 1970s				BCS, 1980s			
	LEA		LEA | Region		DHA		DHA | Region	
	Years	A Levels+	Years	A Levels+	Years	A Levels+	Years	A Levels+
Standardised parental education only	0.384 (0.011)	0.145 (0.006)	0.383 (0.011)	0.145 (0.006)	0.386 (0.011)	0.198 (0.009)	0.381 (0.012)	0.197 (0.010)
Standardised area measure only	0.106 (0.010)	0.040 (0.005)	0.119 (0.014)	0.048 (0.007)	0.106 (0.011)	0.046 (0.006)	0.108 (0.013)	0.049 (0.007)
Standardised parental education | area	0.377 (0.011)	0.143 (0.006)	0.378 (0.011)	0.143 (0.006)	0.378 (0.011)	0.194 (0.009)	0.374 (0.012)	0.194 (0.010)
Standardised area | parents	0.057 (0.009)	0.023 (0.005)	0.066 (0.013)	0.029 (0.007)	0.047 (0.010)	0.021 (0.006)	0.055 (0.012)	0.027 (0.007)
	9587	8003	9587	8003	7185	7159	6333	6319
Percentage of intergenerational mobility attributable to area	1.8%	1.4%	1.3%	1.4%	2.1%	2.0%	1.8%	1.5%
Percentage of area effect attributable to parents	46.2%	42.5%	44.5%	39.5%	55.7%	54.3%	49.1%	44.9%

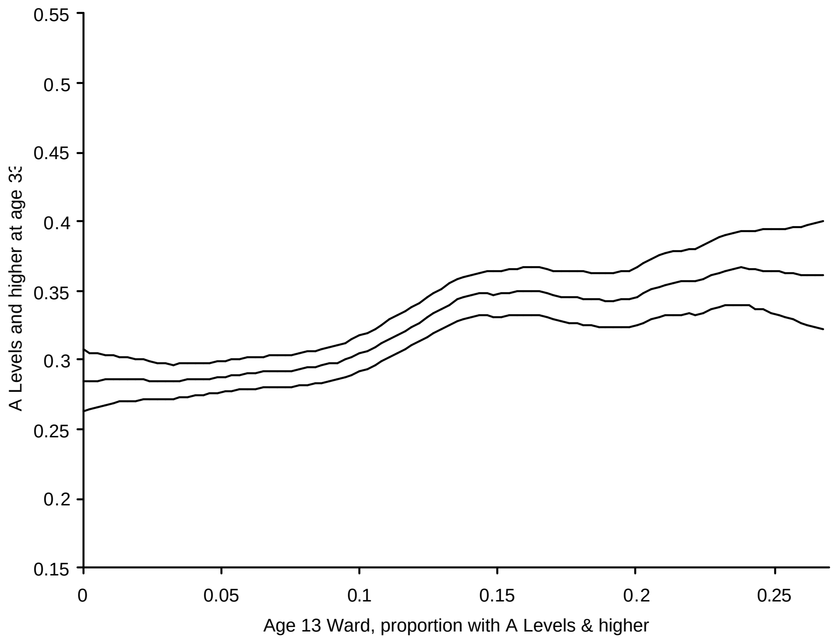
Proportion with A-levels plus in BCS, 1996 is 39.2%.

Figure 1: Attainments and childhood neighbourhood; semi-parametric estimates

a) County controls only



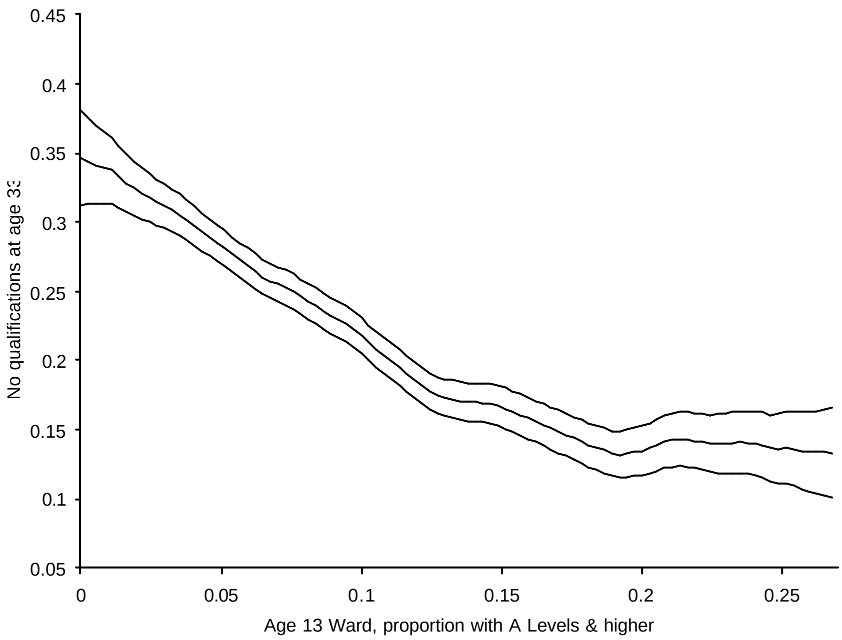
b) Controlling for parental and other locational characteristics in partial linear model



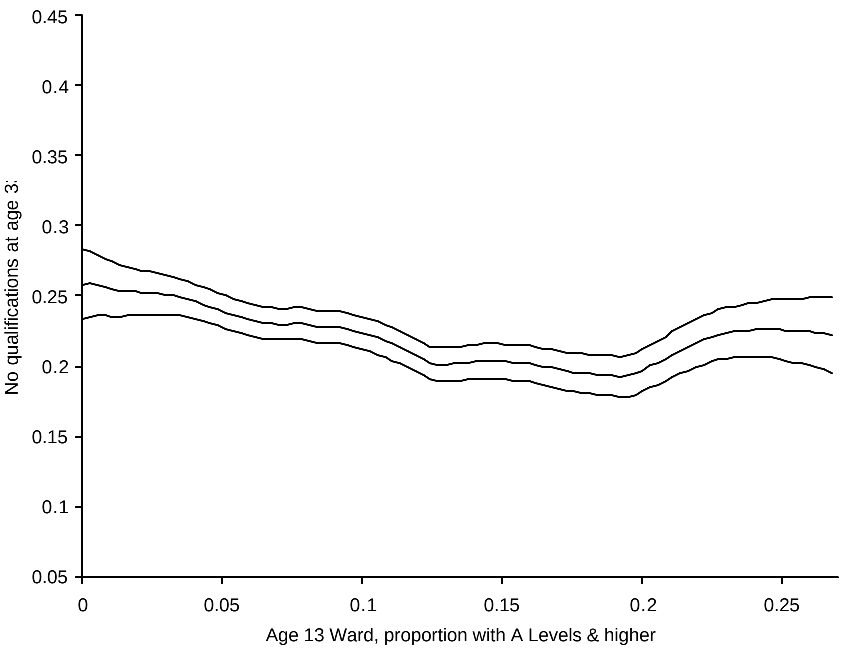
Figures show kernel regressions of age 33 qualifications on childhood neighbourhood status. Controls in figure 1b) are parental education, family size, father's age, residential tenure, rooms in family home, mean age 7 test scores, local authority agricultural employment, unemployment rate and county dummies. Epanachikov kernel, bandwidth by Silverman's rule. 10% pointwise confidence intervals shown. 10th, 50^{th,} 90th percentiles of neighbourhood measure = 0.037, 0.095, 0.216. N=9279.

Figure 2: Attainments and childhood neighbourhood: semi-parametric estimates

a) County controls only



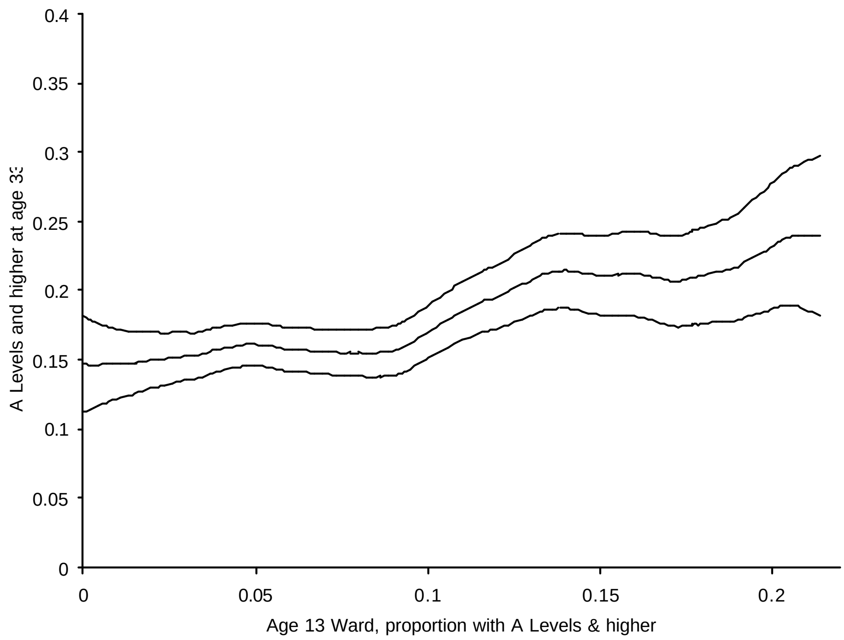
b) Controlling for parental and other locational characteristics in partial linear model



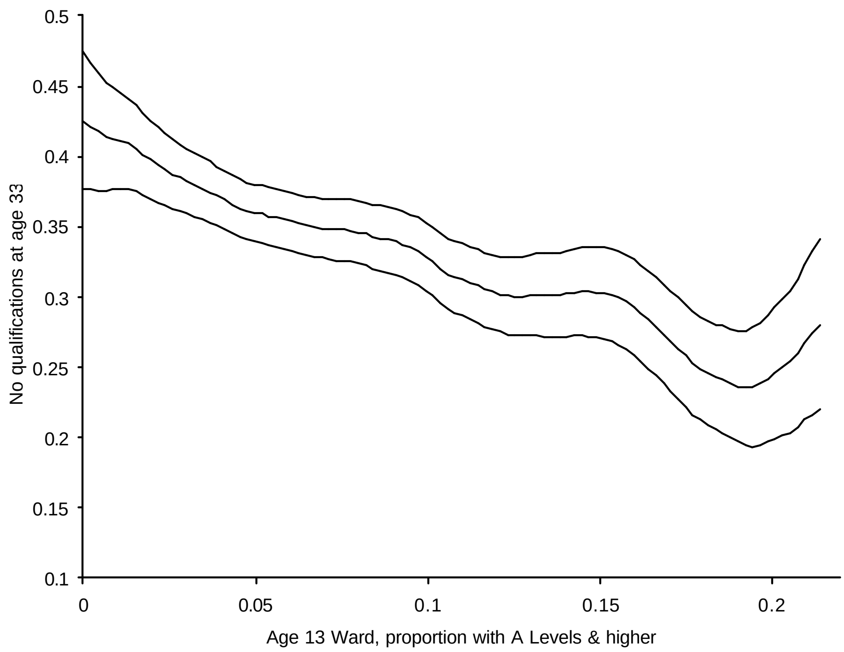
Figures show kernel regressions of age 33 qualifications indicator on childhood neighbourhood status. Controls in figure 1b) are parental education, family size, father's age, residential tenure, rooms in family home, mean age 7 test scores, local authority agricultural employment, unemployment rate and county dummies. Epanachikov kernel, bandwidth by Silverman's rule. 10% pointwise confidence intervals shown. 10^{th}, $50^{th,}$ 90^{th} percentiles of neighbourhood measure = 0.037, 0.095, 0.216.

Figure 3: Attainments of social tenants: semi-parametric estimates

a) A Levels and higher, county controls only

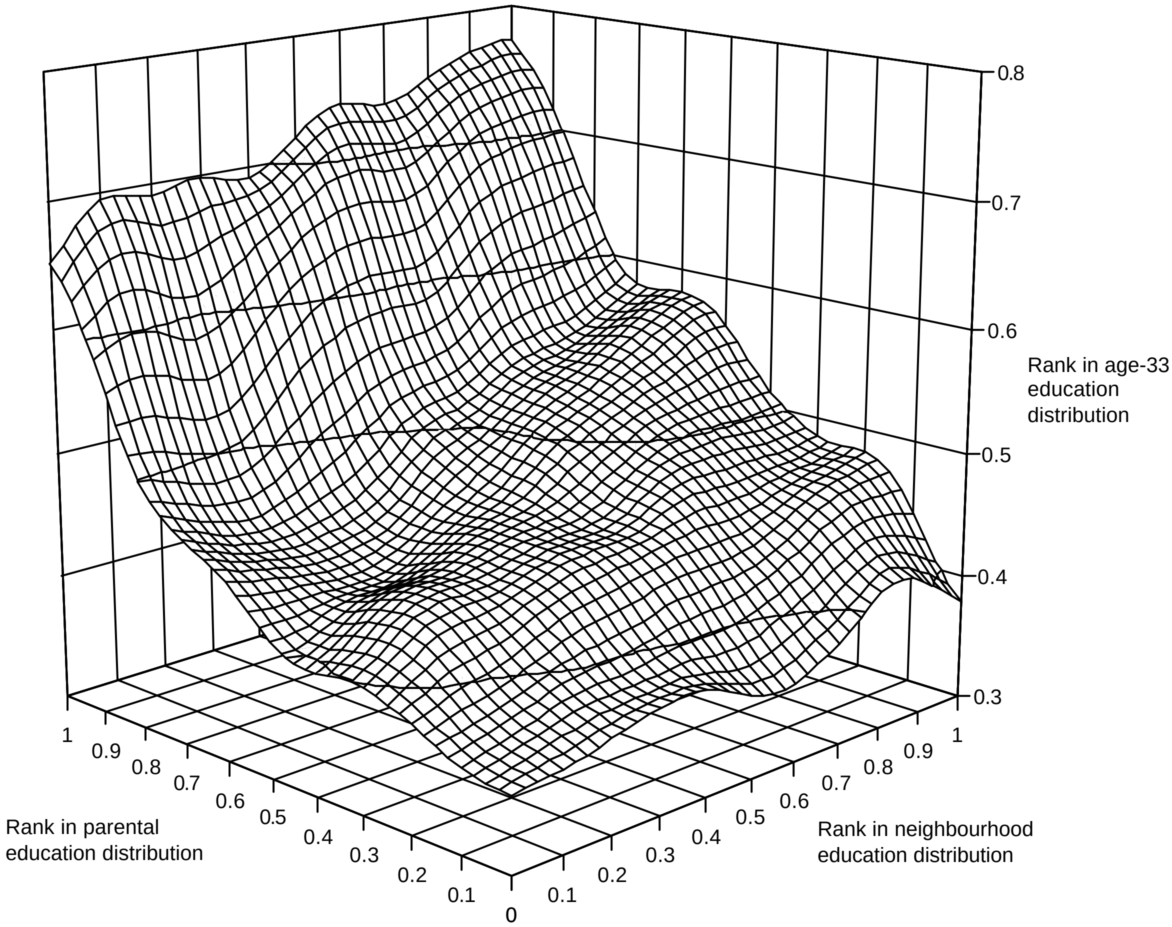


b) No qualifications, county controls only



Figures show kernel regressions of age 33 qualifications indicator on childhood neighbourhood status. Epanachikov kernel, bandwidth by Silverman's rule. 10% pointwise confidence intervals shown. 10^{th}, $50^{th,}$ 90^{th} percentiles of neighbourhood measure = 0.030, 0.077, 0.175. N = 3418.

Figure 4: Educational intergenerational mobility and neighbourhood



Appendix A

A.1 Dependent variables

This Appendix describes the dependent variables used in the main tables. Tables under each heading present summary statistics for the base samples used in the regressions.

Highest qualification at age 33: A 3-category qualifications variable derived from the 1991 cohort member interview, taking the values:

Category	Description	Men	Women
Low qualifications	No qualifications, or qualifications below CSE-grade 1	18.7%	24.1%
Mid qualifications	O-levels, CSE grades 1 or more, lower and intermediate vocational qualifications (City and Guilds, BTEC etc.)	47.5%	43.9%
High qualifications	A-levels, higher vocational qualifications (Higher National Diplomas, teaching and nursing qualifications), First Degrees and equivalent, or Higher Degrees	33.8%	32.1%

NCDS cohort member test scores: Age 16 abilities are measured by a reading comprehension test devised by National Foundation for Educational Research, specifically for the NCDS and a mathematics comprehension test constructed by the same organisation. The reading test is heavily left skewed with the first quartile at 0.63.

	Observations	Mean	S.D.	Minimum	Maximum
Reading	8304	0.743	0.187	0.029	1
Arithmetic	8277	0.427	0.225	0	1

A.2 Family background variables

Education: Education of the persons recorded as the father and mother figure in 1974. Codes as age left full-time education from 1974 sweep, or derived from data on whether father figure in 1965 stayed on at school and age left school. These education variables are recoded as a 3-category variable: 15 and under, 16-18, 18+ for use in the early attainment models.

Family size: Coded as maximum children under 21 recorded over all sweeps of the NCDS up to 1974. Enters as natural logarithms in regressions.

House size: Number of rooms in family residence recorded in 1974, or 1969 if missing, or 1965 if missing from both

	Observations	Mean	S.D.	Minimum	Maximum
Father education	11336	15.14	1.99	12	32
Mother education	11336	15.02	1.46	12	23
Number of children	11336	3.29	1.70	1	14
Father's age	11336	30.59	6.25	12.99	78.00
House rooms	11336	4.93	1.39	1	32

Parental interest in their child's education: coded as a 12-category, non-ordered variable. The categories are:

Parental interest	Read to child age 7	Proportion
Mother or Father very interested, all years	No	1.78
Mother or Father very interested, all years	Yes	3.56
Mother or Father very interested, two sweeps	No	8.57
Mother or Father very interested, two sweeps	Yes	14.35
Mother or Father very interested, one sweep	No	16.21
Mother or Father very interested, one sweep	Yes	20.13
Some, or various interest recorded	No	11.12
Some, or various interest recorded	Yes	11.43
Mother or Father very interested, one sweep	Unknown	4.69
Some, various or little interest recorded	Unknown	4.04
Little interest by mother and father for at least two sweeps	No	2.36
Little interest by mother and father for at least two sweeps	Yes	1.76

Tenancy group: recorded in 1974, or 1969 if missing, or 1965 if missing from both.

	Proportion
Owner-occupier	3.89%
Local Authority tenant	48.52%
Private tenant	39.08%
Tied, or other accommodation	5.02%
Missing	3.89%

A.3 Schooling variables

School quality: measured as the proportion of boys or girls aged 15 in the child's secondary school studying for GCE and SCE O-Levels.

	Observations	Mean	S.D.	Minimum	Maximum
Boys	9007	0.259	0.332	0	1
Girls	9012	0.259	0.333	0	1

Secondary school type: at age 16 is categorised as follows:

	Proportion
Comprehensive	58.5%
Grammar	11.5%
Secondary modern	21.9%
Independent	3.3%
Grant maintained	2.4%
Other, non-lea	2.5%

A.4 Area variables

1971	Mean	S.D.	Minimum	Maximum
Ward proportion with A levels +	0.114	0.078	0.000	0.733
Ward proportion unskilled	0.074	0.044	0.000	0.050
Ward unemployment	0.041	0.022	0.002	0.353
Ward proportion males econ active	0.606	0.051	0.250	1.000
Ward proportion females econ active	0.575	0.121	0.000	1.000
Ward New-Commonwealth immigrants	0.029	0.075	0.000	0.776
Ward proportion 1 year migrants	0.093	0.045	0.000	0.667
Ward mean rooms per household	4.849	0.566	2.190	7.750
Ward proportion lacking toilet or bath	0.029	0.029	0.000	0.222
Ward social housing	0.354	0.266	0.000	1.000
Local authority agricultural employment	0.025	0.057	0.000	0.663
Local authority mining & manufacturing	0.374	0.130	0.000	0.725
Total population (1000s)	9.858	8.070	0.278	82.276

A.4.1 Persistent labour market and LEA funding controls

I make the assumption that local labour markets and local educational expenditures are effective at county level, and use dummy variables to indicate county of residence at age 16 (or county of residence at age 23 for the models of NCDS member's children's attainments). This implies county of origin effects in the determination of adult human capital and early academic achievements.

As controls for educational spending, these effects are consistent with uniform spending within local education authorities in Great Britain, except in the metropolitan areas where spending may be more localised. Using LEA dummies makes little difference. Initial estimates were made using measures of LEA spending on secondary education in 1974 (child age 16), but the results suggest that this measure is endogenous due to prescriptive allocation of educational resources, with significant negative correlations between educational attainments and LEA spending.

The claim that county of origin dummies are adequate controls for local labour markets rests on the assumption that the cohort members are at least mobile within counties, between childhood and age 33. If labour markets are more localised, and there are significant fixed costs to moving from the parental neighbourhood, then the neighbourhood educational variable may still be endogenous. Low local demand for skills during childhood may mean low local demand for skills in adulthood if individuals are geographically immobile. This will almost certainly be true in rural communities where agricultural employment is relatively high. In addition to the county dummies I include from the Census, the proportion of workers in agricultural employment in the Local Authority area.

A.4.2 Population, urban and rural effects

We have good reason to believe that the magnitude of the influences of neighbourhood will vary with neighbourhood population or population density, and that there will be differences between rural and urban areas. A richer network of contacts and proximity to others in a densely populated area may lead to stronger influences from others in the neighbourhood. Then again, the complexity of influences in a highly populated neighbourhood may break down any intergenerational links, whilst simpler structures in sparsely populated rural communities may encourage them. Differences in environmental influences between highly urbanised, metropolitan areas and others may influence occupational and educational choices.

Unfortunately it is not possible to construct exact population density measures with the available 1971 Census data. Instead I include a high (top 20%) ward population indicator, which will proxy high population density if ward areas are less variable than the populations.

The regressions also include a city indicator, which defines all those Census districts listed as ‘C.B.’ (major cities and towns in England and Wales), ‘L.B.’ (London Boroughs), and ‘Cities’ in Scotland. Around 40% of the NCDS sample were resident in such districts in 1971. Unsurprisingly the correlation between the city and high population indicators is fairly high (0.43 in the whole NCDS sample, 0.49 in the selected male subsample).

Children brought up in agricultural areas will have obvious incentives to continue in agricultural work. Failure to control for agricultural employment will bias results in favour of finding neighbourhood effects on educational choices. One solution would be to exclude all those in agricultural jobs from the sample, at the expense of sample representativeness. The alternative, adopted in this paper, is simply to include a variable indicating the proportion of workers in agricultural employment in the childhood Local Authority area, taken from the 1971 Census. In fact, only 2% of the male subsample are in agricultural employment at age 33 and these can be omitted without changing the results significantly.

Appendix B

Table 10: Area-only models of women's, age 33 qualifications

	I			II			
	Low	High	| t |	Low	High	| t |	Mean
Ward education	-0.570	0.655	6.236	-0.440	0.500	4.476	0.116
School quality	-	-	-	-0.393	0.445	21.024	0.272
Unskilled workers	0.259	-0.297	1.466	0.170	-0.193	0.883	0.074
Unemployment rate	0.912	-1.047	2.515	0.591	-0.670	1.593	0.040
Economically active males	0.028	-0.032	0.288	-0.052	0.057	0.485	0.606
Economically active females	0.070	-0.081	1.249	0.033	-0.037	0.555	0.575
One year migrants	0.056	-0.065	0.512	0.023	-0.026	0.196	0.094
New com. immigrant	-0.147	0.169	1.845	-0.160	0.181	1.867	0.028
Average dwelling size	-0.004	0.005	0.271	0.014	-0.016	0.805	4.864
Household lacking amenities	0.537	-0.617	1.872	0.610	-0.692	2.022	0.028
Social housing	0.119	-0.136	3.515	0.113	-0.128	3.167	0.396
City ward	-0.027	0.031	1.831	-0.005	0.006	0.319	0.408
High population	-0.001	0.002	0.098	-0.001	0.002	0.094	0.245
Agricultural employment	-0.009	0.010	0.074	0.000	-0.000	0.004	0.026
Mining, manufacturing employment	-0.008	0.009	0.128	0.015	-0.017	0.225	0.370
County effects	χ^2_{60} = 97.17, P = 0.002			χ^2_{60} = 114.52, P = 0.000			
Predicted group probability	0.240	0.321		0.232	0.329		
Log likelihood		-4967.89			-3794.69		
Pseudo R^2		0.039			0.096		
Sample size		4835			3937		

Including ward professional and managerial employees reduces parameter on ward education to –0.278/+0.315 in column II (t=2.335). Coefficient on professional workers is almost identical (t=2.265).

Neighbourhood educational measure is proportion of adults in high qualification category in cohort member's age-13 residential ward. School quality is proportion of girls age 15 studying for GCEs at cohort members' school.

Table 11: Neighbourhood education and family effects on women's age 33 qualifications

	I			II			III			
Qualification group:	Low	High	| t |	Low	High	| t |	Low	High	| t |	Mean
Ward education	-0.147	0.176	2.61	-0.133	0.154	2.02	-0.142	0.163	2.15	0.117
School performance	-	-	-	-0.174	0.202	10.24	-0.093	0.107	4.10	0.272
School type:	-	-	-	-	-	-	χ^2_5 = 32.35, P=0.0000			
Grammar	-	-	-	-	-	-	-0.093	0.106	5.04	0.138
Secondary modern	-	-	-	-	-	-	0.012	-0.014	1.02	0.211
Independent	-	-	-	-	-	-	-0.043	0.049	1.52	0.033
Grant maintained	-	-	-	-	-	-	-0.113	0.129	2.97	0.026
Other non-LEA	-	-	-	-	-	-	0.036	-0.041	1.06	0.019
Mother education yrs	-0.024	0.028	6.10	-0.022	0.025	5.51	-0.021	0.024	5.34	15.108
Father education yrs	-0.013	0.016	4.46	-0.010	0.012	3.42	-0.010	0.011	3.21	15.218
Father's age	-0.001	0.002	1.83	-0.001	0.001	1.07	-0.001	0.001	1.03	30.694
Dwelling size	-0.004	0.004	1.10	-0.001	0.002	0.43	-0.001	0.001	0.34	4.968
Tenure:	χ^2_4 = 63.04, P=0.000			χ^2_4 = 56.07, P=0.000			χ^2_4 = 55.16, P=0.000			
Tenure missing	0.089	-0.106	3.22	0.093	-0.108	3.11	0.092	-0.105	3.12	0.021
Council tenant	0.081	-0.097	7.67	0.087	-0.101	7.22	0.087	-0.100	7.15	0.380
Private rental	0.048	-0.057	2.21	0.048	-0.056	2.25	0.047	-0.053	2.18	0.043
Other tenure	0.022	-0.026	0.96	0.027	-0.032	1.15	0.028	-0.032	1.16	0.034
Parental interest	χ^2_{11} = 230.22, P=0.000			χ^2_{11} = 208.29, P=0.000			χ^2_{11} = 204.03, P=0.000			
Family size (ln kids)	0.054	-0.064	5.69	0.052	-0.060	5.38	0.052	-0.059	5.40	1.056
Age-7 test scores	-0.690	0.823	19.28	-0.616	0.714	17.01	-0.591	0.677	16.23	0.545
Age-7 tests missing	-0.394	0.470	13.93	-0.347	0.402	12.17	-0.331	0.379	11.55	0.102
Local social housing	0.023	-0.028	0.16	0.002	-0.002	0.16	0.002	-0.002	0.135	0.400
City ward	-0.015	0.018	1.30	-0.010	0.011	0.76	-0.012	0.014	0.96	0.405
High population	-0.028	0.033	2.15	-0.024	0.028	1.92	-0.023	0.027	1.83	0.241
LA agriculture	-0.075	0.090	1.09	-0.079	0.091	0.76	-0.092	0.106	1.06	0.026
LA unemployment	0.819	-0.977	2.28	0.748	-0.868	2.05	0.735	-0.842	2.00	0.041
County effects	χ^2_{60} = 112.32, P=0.000			χ^2_{60} = 92.39, P=0.005			χ^2_{60} = 92.76, P=0.004			
Mean	0.232	0.328		0.233	0.328		0.233	0.328		
Log likelihood	-3317.91			-3266.22			-3249.81			
Pseudo R^2	0.210			0.222			0.226			
Sample size	3937			3937			3937			

Neighbourhood educational measure is proportion of adults in high qualification category in cohort member's age-13 residential ward.

School performance is proportion of girls age 15 studying for GCEs.

Other variables as in Table 2.

Estimation of model of first column using full available sample of 4835 women gives marginal effect from neighbourhood education of – .129 on the low category and .150 on the high category (t = 2.158, p-value = 0.031). The coefficient is not significantly different from estimate on the smaller subsample for which school performance is observable.

Appendix C

For completeness, Table 12 shows comparable results for the non-socially housed group. As expected, given the sorting of this group into neighbourhoods along educational lines, the basic coefficients are much higher than for the socially housed group. The elasticity for the high qualifications category is 0.3 in column I, 0.168 in column II once we control for secondary school quality. Looking at equation (17), we can use the social housing proportion as an instrument for owner-occupier and private tenant's neighbourhoods if we are prepared to assume that this is not correlated with the educational attainments of adults in these groups. Columns III and IV apply this method. The resulting elasticities are 0.249 without, and 0.143 with predicted secondary school quality. The difference highlights the likelihood that the instrument is not uncorrelated with school characteristics – secondary modern technical schools are more likely sited near council estates for example. Even so, if the proportion in social housing is uncorrelated with other unobserved determinants of owner-occupiers' and private tenants' children's attainments then the estimate in column IV is consistent.

Table 12: Neighbourhood education effects on non-social tenants, age 33 qualifications

	I			II			III			IV			
Qualification group:	Low	High	| t |	Low	High	| t |	Low	High	| t |	Low	High	| t |	Mean
Ward education	-0.576	1.02	11.78	-0.317	0.553	7.15	-0.459	0.820	7.27	-0.268	0.468	3.62	0.130
School quality	-	-	-	-0.199	0.347	18.03	-	-	-	-0.287	0.500	18.76	0.300
Early attainments	-	-	-	-0.567	0.990	21.74	-	-	-	-0.498	0.869	21.00	0.555
Missing	-	-	-	-0.352	0.615	18.56	-	-	-	-0.309	0.539	18.19	0.115
Male	-0.007	0.012	1.01	-0.017	0.030	2.67	-0.007	0.012	0.94	-0.015	0.027	2.37	0.486
City ward	-0.009	0.016	0.84	-0.004	0.006	0.38	-0.008	0.014	0.79	-0.000	0.001	0.05	0.385
High population	-0.012	0.021	1.16	-0.013	0.022	1.35	-0.012	0.022	1.15	-0.012	0.020	1.19	0.222
LA agriculture	0.095	-0.168	1.34	0.101	-0.176	-1.64	0.105	-0.188	-1.46	-0.114	0.199	-1.67	0.029
LA unemployment	1.075	-1.911	3.32	0.829	-1.447	-2.89	1.210	-2.163	4.03	0.802	-1.400	-2.84	0.038
County effects	χ^2_{60} = 91.61, P=.0054			χ^2_{60} = 111.70, P=0.0001			χ^2_{60} = 101.30, P=0..0007			χ^2_{60} = 110.03, P=0.0000			
Exogeneity test	-			-						χ^2_{5} = 7.327, P=0.1974			
Predicted group prob.	0.137	0.428		0.137	0.428		0.137	0.428		0.137	0.428		
Log likelihood	-4581.57			-4015.58			-4747.91			-.4039.08			
Pseudo R^2	0.034			0.153			.020			0.148			
Sample size	4749			4749			4749			4749			

Three category ordered probit estimates.

Predicted neighbourhood education uses the proportion of local authority tenants in the cohort members' age-13 ward as instrument.

Inclusion of parental education gives marginal effects of –0.35/+0.60 in column 1 (t = 7.50); inclusion of parental interest dummies in column 1 gives –0.26/+0.46 (t = 5.892).

School quality is proportion of own sex, age 15 studying for GCEs, instrumented by school type and pupil-teacher ratio to remove catchment area effects on school quality (but not peer group effects or correlation between pupil performance due to selection by schools or by parents). Early attainments measure tests sensitivity to selection on ability to high performing schools, by schools or parents – without early attainment control estimates in column 4 are -.392, .666 for school quality parameter, -.326, .554 for neighbourhood parameter.

Instruments have p -value < 0.01% in prediction equations.

Appendix D

Any discussion of neighbourhood effects from adult outcomes presupposes that neighbourhoods differ in their composition, in terms of the characteristics of residents. Figure 5 shows to what extent the educational composition of residents varies across Census wards in Britain, and charts the changes that have taken place between the 1971 to 1991 Census. Both panels show kernel density estimates of the distribution of the proportion of qualified residents across Census wards. The proportions are computed as the proportion of qualified residents aged 18 and over for 1971 and 1991[21]. Panel 1 compares the 1971 and 1981 distributions. Panel 2 compares the 1981 and 1991 distributions.

A couple of points should be borne in mind when interpreting the diagrams. Firstly they are based on the Census numbers taken from the 10% Census samples, which are subject to sampling error, so the observed variance may overstate the true variance across wards. Secondly the 1971 and later Census years are not strictly comparable, because of major changes in the Census geography. Variation in the level of disaggregation will change the observed variance, even if there were no underlying changes in the degree of segregation. In the extreme case of observations on individuals, the distribution would be bi-modal with peaks at 0 and 1, whilst at the other extreme of a single observation for Britain, the distribution would be degenerate at the national mean. Wards in 1981 and 1991 were, on average, larger than in 1971, so the estimated density function will appear compressed relative to the density based on 1971 wards.

Looking at the figures, it seems there has been a flattening and rightward shift in the distribution of qualifications across wards over time. The density estimate for the proportion with degrees and similar qualifications in 1971 is sharply peaked relative to the curve in 1981. In 1981, the distribution of degrees across wards was closer to the distribution of A-levels and higher qualifications in 1971 – evidence of the general upgrading of qualifications that has taken place over the last decades.

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[21] No figure for the number of residents age 18 and over is available for the 10% sample in 1981. The denominator used here is the number of residents in the 10% sample, weighted by the proportion of residents aged 18 and over, taken from the 100% sample.

Standard measures of inequality suggest that this observed spread in the density does not reflect increasing inter-ward inequality attributable to increasing segregation along educational lines. In 1971 the mean proportion of residents with degrees and similar qualifications was only 6.4% with a standard deviation of 5.4%. By 1981, the proportion with these qualifications had increased to 10.7%, with a standard deviation of 6.6%. By 1991, the proportion was up to 14.3%, with a standard deviation of 8.2%. Using the coefficient of variation as a measure of inter-ward inequality, this implies a decrease from 0.84 to 0.62 to 0.57 over the years covered by the Census. An alternative measure, which may be preferable in this case where the distribution is highly skewed, is the $90^{th}/10^{th}$ percentile ratio. This tells a similar story, with a decrease from 7.4 in 1971 to 5.79 in 1981 to 5.1 in 1991. Even if we disqualify the 1971 Census because of the different Census geography, there is no evidence of increasing inequality in the ten years between 1981 and 1991.

In fact, the change in the distribution may be almost entirely attributable to the general growth in the proportion of qualified individuals from one cohort to the next. If we re-scale the numbers by dividing by the mean proportion in each year, so that the means are normalised to 1, we find that the empirical densities for 1981 and 1991 are almost identical. The 1971 line is also fairly close – see Figure 6.[22] A constant multiplicative increase in the qualified proportion in each ward widens the distribution because wards with few qualified people show a smaller absolute increase than wards with many qualified people. By contrast, if there is increasing segregation, then wards at the lower end of the distribution will show smaller proportional increases than those at the mean, because individuals with low qualifications migrate to these wards and more educated people leave. Wards at the top end would show larger proportional increases than average as highly educated individuals became concentrated in these wards over time.

It has been claimed by Wilson (1987) and others that neighbourhood segregation in the US is increasing, with a consequent widening of the distribution of skills and education across neighbourhoods (see Brooks-Gunn *et al*, 1993). There is no evidence that this is a significant phenomenon in Britain, based on this ward level Census data on qualifications. This is not to say that we would not find evidence of segregation at lower levels of

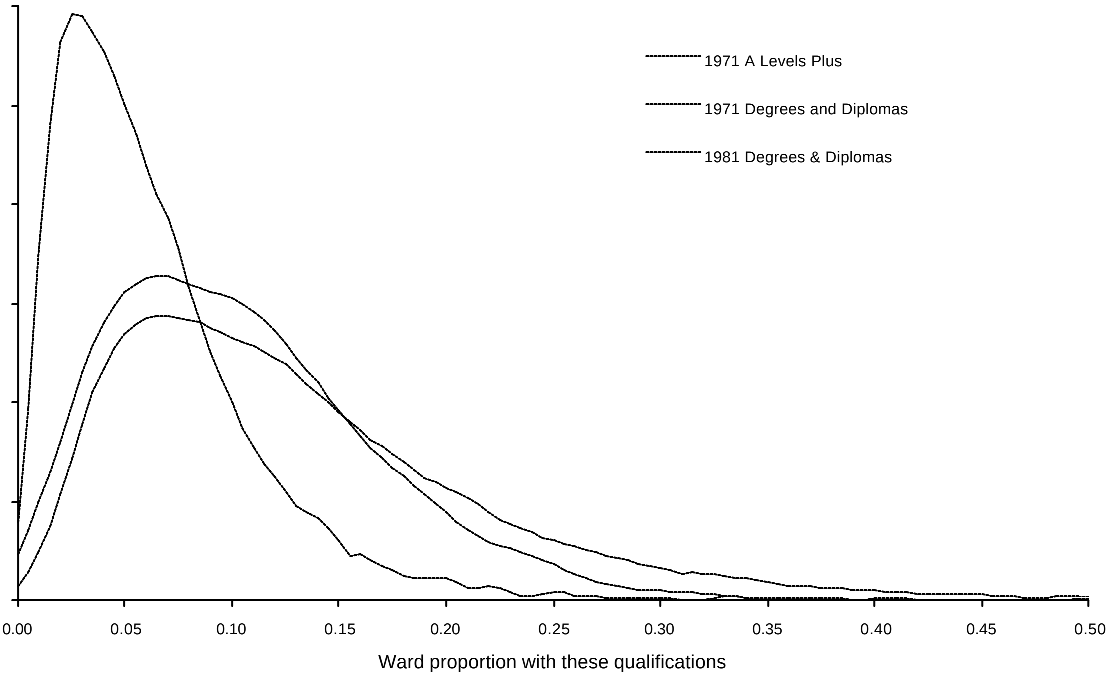
[22] The same effect is observed if we take logs of the proportions and subtract the transformed mean.

disaggregation – segregation could increase over the years within wards, whilst leaving the distribution across wards unchanged. Unfortunately, the output of the qualifications variables from the Census at the more disaggregated enumeration district level is of little use due to the high sampling errors from the 10% sample and cannot be used to check this. It is also plausible that convergence between broader geographical groups may have obscured increases in inter-ward inequality. To test this, Figure 7 shows the kernel densities for 1981 and 1991, based on the deviation of the ward proportion with qualifications from the mean in the district to which the ward belongs (there are around 500 Census districts in Great Britain). Panel 1 shows a widening of the distribution across wards, within districts. If, however, we scale the data to allow for the change in the national mean proportion of qualified residents – see Panel 2- we find little visual evidence of any underlying change across wards.[23]

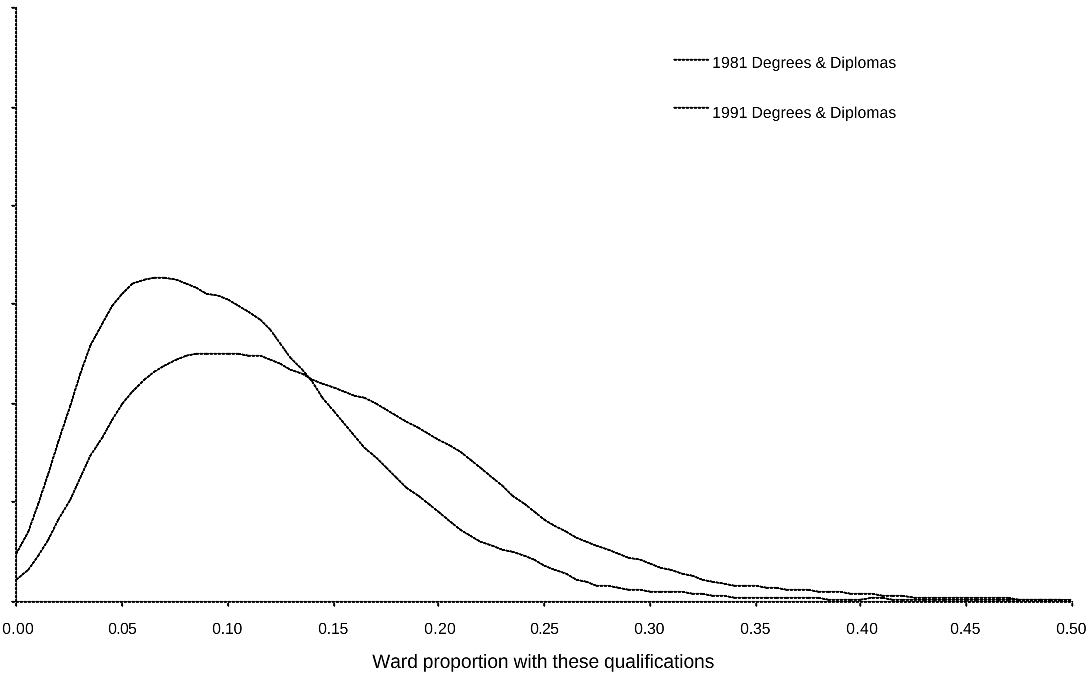
[23] If we do the same using characteristics which are measured accurately at ED level – residential overcrowding or unemployment rates – there is still no evidence of increased spatial inequalities. The kernel densities for the ED proportions in unemployment and persons per room in 1981 and 1991, or the deviations of these from ward means, are almost exactly overlying.

Figure 5: Changes in the spatial distribution of education

a) 1971 and 1981



b) 1981 and 1991

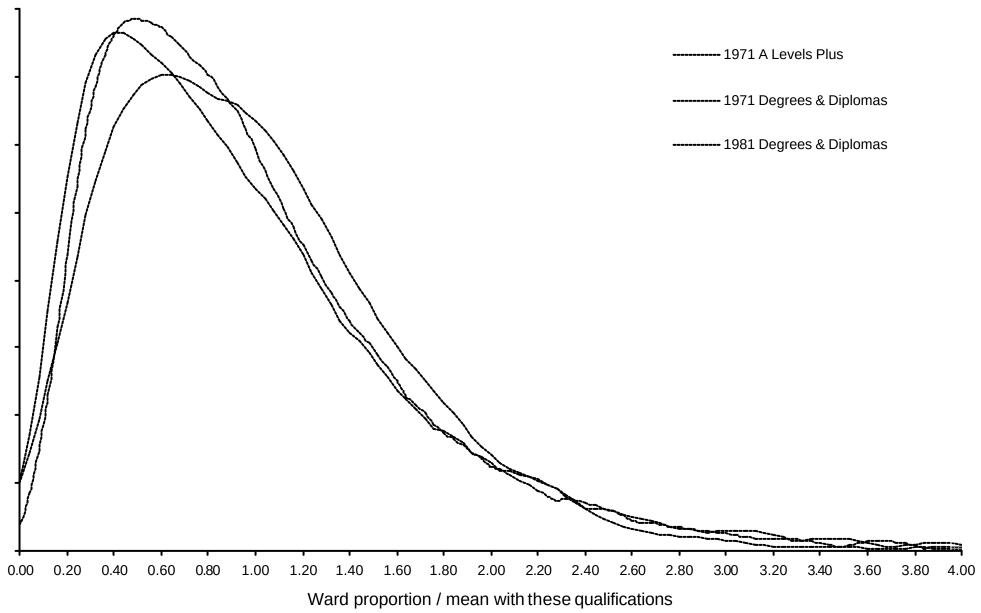


Figures show kernel densities of the proportion of residents with high qualifications in Census wards, 1971, 1981 and 1991. High qualifications are degrees, diplomas and professional qualifications.

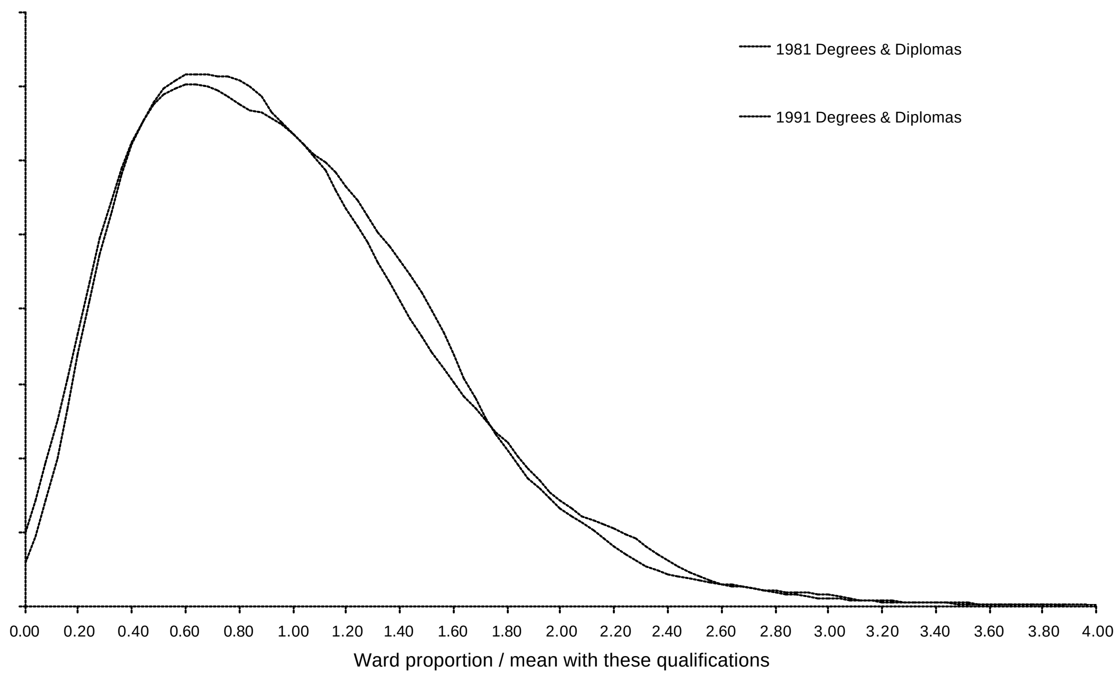
Distribution of proportion with A-levels, degrees, diplomas and professional qualifications shown for 1971.

Figure 6: Changes in the spatial distribution of education, mean adjusted

a) 1971 and 1981



b) 1981 and 1991

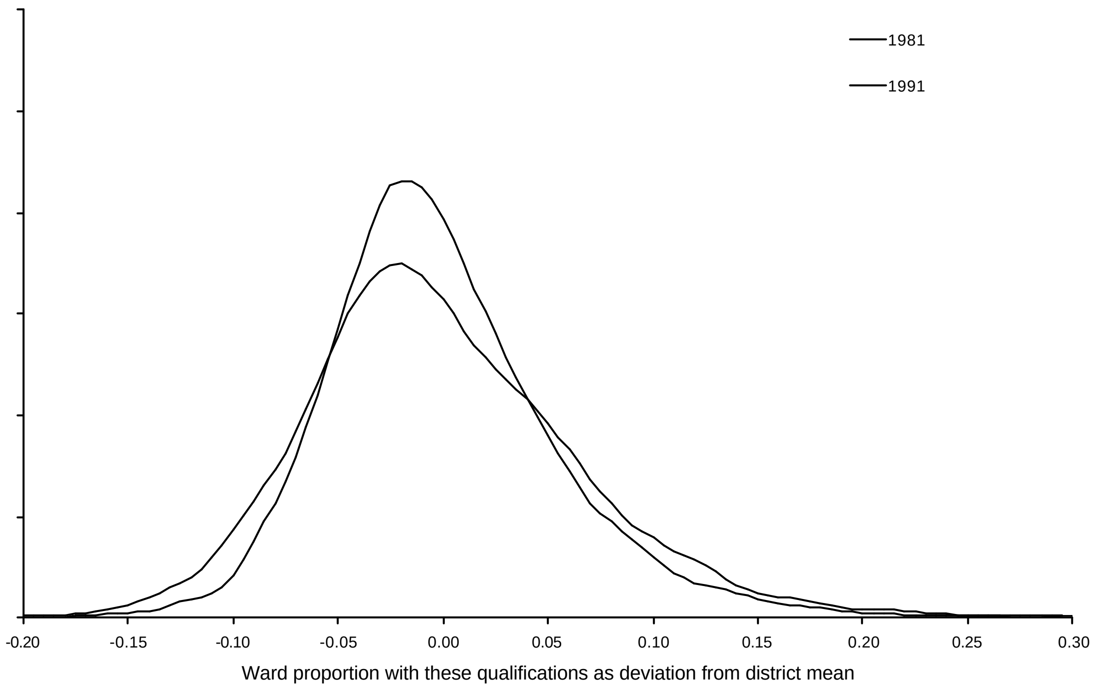


Figures show kernel densities of the proportion of residents with high qualifications in Census wards, 1971, 1981 and 1991. High qualifications are degrees, diplomas and professional qualifications.

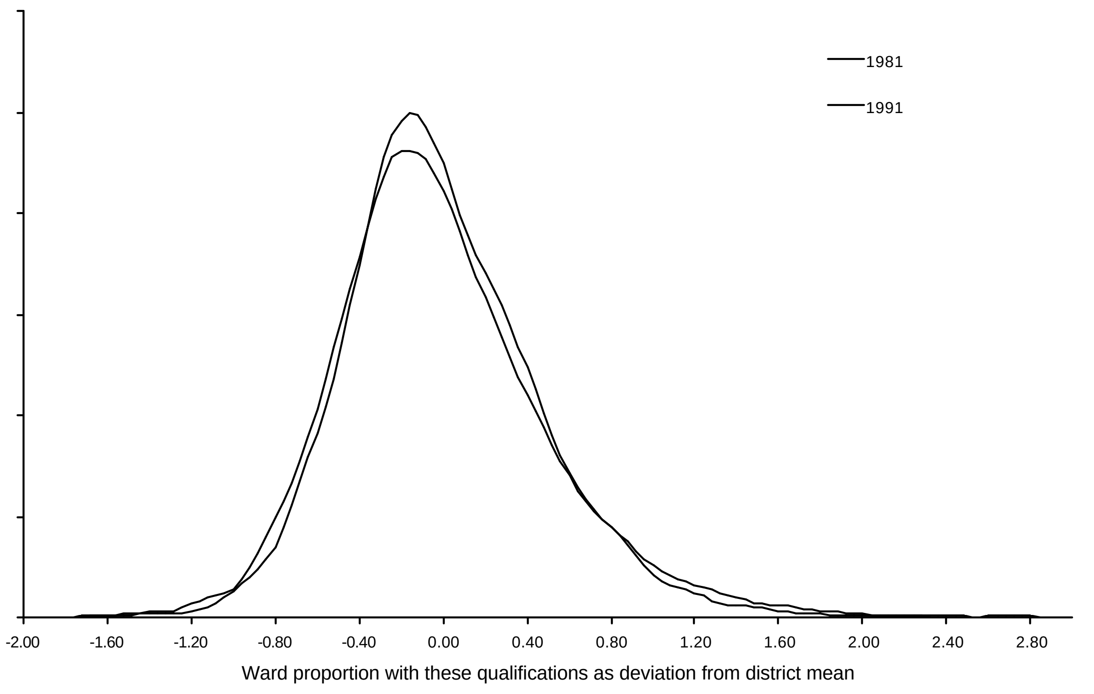
Distribution of proportion with A-levels, degrees, diplomas and professional qualifications shown for 1971.

Figure 7: Changes in the within-district spatial distribution of qualified residents

a) 1981 and 1991



b) 1981 and 1991, mean adjusted



Figures show kernel densities of the proportion of residents with high qualifications in Census wards, 1971, 1981 and 1991. High qualifications are degrees, diplomas and professional qualifications.

Distribution of proportion with A-levels, degrees, diplomas and professional qualifications shown for 1971.

References

Angrist, J. D. and Imbens, G. W. (1994), 'Identification and Estimation of Local Average Treatment Effects', Econometrica 62(2): pp.467-475.

Atkinson, A. (1981), 'On Intergenerational Income Mobility in Britain', Journal of Post Keynsian Economics 3: pp.194-218.

Benabou, R. (1996), 'Equity and Efficiency in Human Capital Investment: The Local Connection', Review of Economic Studies, 63(2), pp.237-264.

Blanden, J., Goodman, A., Gregg, P. and Machin, S. (2001), 'Changes in Intergenerational Mobility in Britain', Centre for Economic Performance Discussion Paper No. 517, London School of Economics.

Borjas, G. J. (1992), 'Ethnic Capital and Intergenerational Mobility', The Quarterly Journal of Economics, pp.123-150.

Borjas, G. J. (1995), 'Ethnicity, Neighborhoods and Human-Capital Externalities', The American Economic Review 85(3): pp.365-390.

Bronfenbrenner, U. (1979), *The Ecology of Human Development*, Harvard University Press: Cambridge, Mass.

Brooks-Gunn, J., Duncan, G. J., Klebanov, P. K. and Sealand, N. (1993), 'Do Neighbourhoods Influence Child and Adolescent Development', American Journal of Sociology 99(2): pp.353-395.

Chase-Lansdale, P. L., Gordon, R. A., Brooks-Gunn, J. and Klebanov, P. K. (1997), 'Neigbourhood and Family Influences on the Intellectual and Behavioural Competence of Preschool and Early School-Age Children', in J. Brooks-Gunn, G. J. Duncan and J. L. Aber (eds.), *Neighborhood Poverty: Context and Consequences for Children*, Russel Sage Foundation: New York.

Coleman, J. (1988), 'Social Capital in the Creation of Human Capital', American Journal of Sociology 94(Supplemement), pp.S95-S120.

Coleman, J. (1994), *Foundations of Social Theory*, Harvard University Press: Cambridge, Mass.

Crane, J. (1991), 'The Epidemic Theory of Ghettos and Neighborhood Effects on Dropping Out and Teenage Childbearing', American Journal of Sociology 96(5): pp.1226-1259.

Datcher, L. (1982), 'Effects of Community and Family Background on Achievement', Review of Economics and Statistics 64(1): pp.32-41.

Dearden, L., Machin, S. and Reed, H. (1997), 'Intergenerational Mobility in Britain', The Economic Journal 107: pp.47-64.

Duncan, G. J. (1994), ‘Families and Neighbours as Sources of Disadvantage in the Schooling Decisions of White and Black Adolescents’, American Journal of Education 103: pp.20-53.

Feinstein, L. and Symons, J. (1999), ‘Attainment in Secondary School’, Oxford Economic Papers 51(3): pp.300-321.

Garner, C. L. and Raudenbush, S. W. (1991), ‘Neighbourhood Effects on Educational Attainment’, Sociology of Education 64(4): pp.251-262.

Gephart, M. A. (1997), 'Neighbourhoods and Communities as Contexts for Development', in J. Brooks-Gunn, G. J. Duncan and J. L. Aber (eds.), *Neighbourhood Poverty: Context and Consequences for Children*, Russel Sage Foundation: New York.

Gibbons, S. (2001), 'Neighbourhood Effects on Reading and Numeracy of British Children', Unpublished PhD chapter, University College London.

Ioannides, Y. M. (1997), 'Nonlinear Neighborhood Interactions and Intergenerational Transmission of Human Capital', Department of Economics, Tufts University.

Jencks, C. and Mayer, S. E. (1990), 'The Social Consequences of Growing Up in a Poor Neighbourhood', in L. E. Lynn, Jr. and M. G. H. McGeary, *Inner-City Poverty in the United States*, National Academy Press: Washington DC.

Jensen, B. and Seltzer, A. (2000), ‘Neighbourhood and Family Effects in Educational Progress’, The Australian Economic Review 33(1): pp.17-31.

Katz, L. F., Kling, J. R., and Liebman, J. B. (2001), ‘Moving Opportunity in Boston: Early Impacts of a Housing Mobility Program’, The Quarterly Journal of Economics, forthcoming.

Kremer, M. (1997), ‘How Much Does Sorting Increase Inequality?’ The Quarterly Journal of Economics, pp.115-139.

Kymlicka, W. (1990), *Contemporary Political Philosophy: An Introduction*, Clarendon Press: Oxford.

Loury, G. (1977), 'A Dynamic Theory of Racial Income Differences', in A. Le Mond (ed.), *Women, Minorities and Employment Discrimination*, Lexington.

Manski, C. F. (1993), ‘Identification of Endogenous Social Effects: The Reflection Problem’, Review of Economic Studies 60: pp.531-542.

McCulloch, A. and Joshi, H. (2000), 'Neighbourhood and Family Influences on the Cognitive Ability of Children in the British National Child Development Study', Institute for Social and Economic Research Woking Papers, University of Essex.

Murphy, K. M. and Topel, R. H. (1985), ‘Estimation and Inference in Two-Step Econometric Models’, Journal of Business and Economics Statistics 3(4): pp.370-379.

Nesheim, L. (2001), 'Equilibrium Sorting of Heterogenous Consumers Across Locations: Theory and Empirical Implications', unpublished manuscript.

Overman, H. G. (2000), 'Neighbourhood Effects in Small Neighbourhoods', Centre for Economic Performance Discussion Paper No. 481, London School of Economics.

Robinson, P. M. (1988): 'Root-N-Consistent Semiparametric Regression.' Econometrica 56, no. 4 931-54.

Roemer, J. E. and Wets, R. J.-B. W. (1994), 'Neighbourhood Effects on Belief Formation and the Distribution of Education and Income', Department of Economics, University of California Working Paper Series, Davis, California.

Rosenbaum, J. (1991), ‘Black Pioneers - Do Their Moves to the Suburbs Increase Economic Opportunity for Mothers and Children’, Housing Policy Debate, 2(4): pp.1179-1213.

Rosenbaum, J., Rubinowitz, L. S. and Kulieke, M. J. (1988), ‘White Suburban Schools' Responses to Low-Income Black Children: Sources of Success and Problems’, Urban Review, 20(1): pp.28-41.

Sampson, R. J. and Byron Groves, W. (1989), ‘Community Structure and Crime: Testing Social Disorganization Theory’, American Journal of Sociology, 94(4): pp.774-802.

Shaw, C. and Mackay, H. (1969), *Juvenile Delinquency and Urban Areas: A Study of Rates of Delinquency in Relation to Differential Characteristics of Local Communities in American Cities*, University of Chigago Press: Chicago.

Solon, G. (1989), ‘Biases in the Estimation of Intergenerational Earnings Correlations’, Review of Economics and Statistics 71: pp.172-174.

Solon, G. (1999), 'Intergenerational Mobility in the Labour Market', in O. Ashenfelter and D. Card (eds.), *Handbook of Labor Economics, 3a*, North Holland: Amsterdam.

Solon, G., Corcoran, M., Gordon, R. and Laren, D. (1991), ‘A Longitudinal Analysis of Sibling Correlations in Economic Status’, Journal of Human Resources, 26: pp.509-534.

Solon, G., Page, M. E. and Duncan, G. J. (2000), ‘Correlations Between Neighbouring Children in Their Subsequent Educational Attainment’, Review of Economics and Statistics, 82(3): pp.383-392.

Streufert, P. A. (1991), 'The Effect of Underclass Isolation on Schooling Choice', Institute for Research on Poverty Discussion Paper, University of Wisconsin-Madison.

Wilson, W. (1987), *The Truly Disadvantaged*, University of Chicago Press: Chicago.